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IDENTIFYING SUBSTITUTE AND COMPLEMENTARY RELATIONSHIPS
REVEALED BY CONSUMER VARIETY SEEKING BEHAVIOR

Leigh McAlister*
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Working Paper No. 1487-83 September, 1983

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ABSTRACT

Several different techniques have been proposed for inferring competitive interrelationships. An important subset of those techniques is based on the assumption that those brands most frequently switched between are the closest substitutes. In product classes in which variety seeking is an important determinant of consumer behavior, this assumption is probably violated. Consumers may switch from one brand to another precisely because the brands are not substitutes. The technique we propose reveals not only which brands substitute for one another, but also which brands are chosen as complements to jointly satisfy the consumers' desire for variety. We also suggest a representation of the results which contrasts substitutability and complementarity and preserves the asymmetry which may occur in competitive interrelationships. We apply the proposed and existing techniques to a collection of consumption histories for a frequently purchased packaged good. The proposed technique is shown to extend the range of insights provided by existing techniques.

IDENTIFYING SUBSTITUTE AND COMPLEMENTARY RELATIONSHIPS

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Product line management requires an understanding of competitive interrelationships in the relevant product class.[1] Such understanding allows the manager to avoid offering multiple products which largely meet the same needs of the same consumers and to spot important niches for which the line currently has no offering. Managers can further exploit their understanding of competitive interrelationships in designing advertising copy, selecting distribution channels and developing cross promotional offers. There is, in fact, no marketing mix decision which does not require an understanding of the relevant competitive interrelationships.

The importance of understanding competition among products has given rise to multiple measurement methodologies. Economists offer cross-price elasticity as a measure of one brand's competitive impact on another. Because of the difficulty of estimating cross-price elasticities, marketers have devised other measurement techniques. An important subset of those techniques, characterized by Day, Shocker and Srivastava (1979) as "behavioral," infer competitive interrelationships from consumer choice. Some techniques take the joint occurence of two brands in a consumer's choice set as an indication of substitutability. Other techniques use brand switching behavior to classify brands as substitutes. Fundamental to most behavioral techniques is the notion that consumers have a need that can best be filled by a single product. The brands selected by a particular consumer

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[1]Day and Shocker (1976) point out the importance of first defining the relevant product class. The appropriate definition of that class depends largely upon the particular decision to be made. We assume that the decision maker has grappled with these issues and has determined the boundaries of the relevant product class.

substitute for one another in filling that need.

We contend that product classes in which variety seeking is an important determinant of consumer behavior will pose problems for existing behavioral techniques. When consumers seek variety they have a composite need that cannot best be filled by a single product. In selecting magazines, a consumer might satisfy her or his desire for news, entertainment, and sports by subscribing to several magazines (McAlister, 1979). In selecting soft drinks, a consumer might want to experience the different flavors provided by both colas and non-colas (McAlister, 1982). We suggest that a variety seeking consumer chooses from the product class to fill a composite need. Having chosen a brand to fill one component of the composite need, the consumer is likely to switch to a different brand to fill a different component of that need.

If a consumer satisfies a composite needs by her or his choices in a product class we can no longer assume that a switch from one brand to another indicates substitutes. To understand the interrelationships among products, we must distinguish between products that are chosen to fill the same component of the composite need and products chosen to provide largely different benefits. We will call brands that jointly meet a composite need "complements" and brands that meet the same component of that composite need "substitutes." We propose a technique for revealing substitute and complementary relationships from brand switching data, based upon a model of consumer variety seeking behavior (McAlister, 1983). We also propose a means of representation which contrasts substitutability and complementarity, describes the relationships between products along a continuum, and allows for asymmetries in competitive effects.

Our proposed representation preserves important information about product competition. Unlike a market partition, which reduces the representation of competition to a dichotomous measure, our representation

preserves the relative competitive intensity among pairs of products. Unlike hierarchical structures and perceptual maps, which impose a symmetric representation of competition between products, our representation allows asymmetric competitive effects. We contend that representing this additional information will lead to richer insights into competitive interrelationships.

Our model maintains information on consumer behavior at the individual level. The aggregation required by market level analysis frequently masks interesting implications of consumer heterogeneity. Our technique allows summary measures of competitive interrelationships to be calculated at any level of aggregation. Such segment level analyses can enhance the information provided by market level analysis.

The purpose of this paper is to demonstrate the insights that our technique can provide beyond those provided by existing techniques. Though our data is from a small, non-representative sample, it is able to illustrate this extension. We would expect the analysis of a larger, more nearly representative sample to confirm this finding.

Complements and Substitutes

Definitions

We appeal to Lancaster's (1971) notion of a product as a bundle of a "want satisfying characteristics" in order to more precisely define the terms of substitute and complement. In particular, we will say that two products are substitutes if they meet largely the same need. Two products are complements if they meet different components of a composite need, and if the consumption of one product stimulates the desire for and consumption of the second product.

The definition above is consistent with the standard notions regarding substitute and complementary products. For example, Henderson and Quandt (1958, p. 29) adopt the following definitions:

> "Two commodities are substitutes if both can satisfy the same need to the consumer; they are complements if they are consumed jointly in order to satisfy some particular need."

Our notion of complementarity does not require the simultaneous, joint consumption of two goods to reveal them as complementary. We suggest that the consumption of some product at an earlier point in time might ultimately stimulate or enhance the subsequent desire for a product providing different characteristics. As an individual in search of variety begins to satiate on the characteristics provided by a caffeinated cola beverage, for example, a non-caffeinated, fruit flavored beverage might become relatively more appealing. Thus, just as the consumption of tea enhances the desirability of lemon in the same consumption occasion, so too might the consumption of cola ultimately stimulate the desire for a non-cola on a subsequent consumption occasion. The consumer wants to experience a wide range of characteristics that can only be satisfied by a portfolio of brands. In the context of our definition, both pairs of items (tea and lemon, cola and non-cola) exhibit complementary relationships.

<u>Existing Measures of Complementarity and Substitutability</u>

Of all the proposed approaches for measuring substitutability and complementarity, cross-price elasticity is probably the most well known and widely accepted. Cross-price elasticity is the percentage change in demand for one product divided by the percentage change in price of the second (given that everything else affecting demand remains the same). A positive cross-price elasticity indicates substitutes. A negative cross-price elasticity indicates complements. Concurrent usage is not necessary to the mathematical definition of cross-price elasticity, nor was it a condition

imposed by Richard Stone (1954) in his empirical study The Measurement of Consumers' Expenditures and Behavior in the United Kingdom, 1920-1938, in which he estimates cross-price elasticities for a wide range of foods and beverages. In concluding, Stone provides a list of reasons for the substitutability and complementarity among products which he observed. Complementarity, he suggests, might be driven by individuals' desire for variety. He states (Stone 1954, p. 408):

> "If the price of one kind of fruit rises, the consumption of it, other things being equal, will fall. So far from leading to a substitition of other fruits for it, the result may be that less is spent on other fruits. In this way the variety of consumption may be maintained and the reduced level of fruit consumption may be compensated nutritionally by a greater consumption of vegetables.

Despite the conceptual appeal of cross-price elasticities, Stigler (1966, p. 33) points out the difficulty of operationalizing such general concepts. Most pairs of products, he maintains, are difficult to classify without direct measurement to determine the sign of the cross-price elasticity.

Since Stone (1954), other empirical investigations of cross-price elasticity have been published (see Deaton and Muellbauer, 1980, for an overview). These studies typically investigate relationships between product classes. Marketers interested in relationships between brands within a product class are seldom able to use this measure. Day, Shocker and Srivastava (1979) attribute this infrequent usage of cross-price elasticities to three problems (Day, Shocker and Srivastava 1979, p. 11):

1. The theoretical context of the measure presumes that there is no response by one firm to the price change of another. This theoretical condition is seldom satisfied in practice.
2. It is a static measure and breaks down in the face of a market characterized by changing product composition.

3. In markets where price changes have been infrequent, or all prices change together, or where factors other than prices have also changed, there is simply not enough information contained in the data to permit valid statistical estimation of the elasticities.

Given the difficulty of directly measuring cross-price elasticities, marketers have resorted to a wide variety of approaches for characterizing competitive interrelationships. These approaches can be classified according to the criterion used to establish the existence of competition between products. In the following development, we are concerned with only those techniques based upon behavioral criteria derived in some fashion from actual choice.[2]

Bass, Pessemier and Tigert (1969), and Fraser and Bradford (1983) investigate purchase timing. Bass, Pessemier and Tigert (1969) assume that similarity in purchase rates reveals substitutability. Their technique, however, leads to some counterintuitive results. Butter and water softener are classified as substitutes. Beer and bleach are classified as complements. Fraser and Bradford (1983) assume that the timing of a household's purchases of one item is influenced by the timing of prior purchases of its substitutes. They do not allow for complements at all.

Other approaches scrutinize brand switching in order to infer competitive interrelationships; for example, the Hendry method (Butler, 1970, 1971; Kalwani and Morrison, 1977; Rubinson, Vanhonacker and Bass, 1980; and Vanhonacker 1980), hierarchical clustering (Rao and Sabavala,

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[2]Many studies make use of some subjective criterion; e.g., substitution in-use (Srivastava, Leone and Shocker, 1981), situational definition (Belk, 1979), and products-by-uses (Stefflre, 1979). These techniques are especially appropriate for identifying any potential lines of competition within the product category. In our approach, we are primarily interested in identifying lines of existing substitutability and complementarity revealed by patterns of actual choice behavior.

1981), and the PRODEGY technique[3] (Urban, Johnson and Hauser, 1983). The objective of these techniques is to partition the market into competitive submarkets. They assume that relatively high levels of switching between products indicates close substitutes. Switching is treated uniformly as an indication of competition. The representations drawn by these techniques are done without regard to any complementary relationships which might exist.

Cross-Consumption Response

We propose to characterize the interrelationships between products using a measure of cross-consumption response.[4] Using individuals' past consumption histories and a model of variety seeking proposed by McAlister (1983), we can measure the degree of substitutability or complementarity between all pairs of products.

The essence of the technique, which we describe briefly in the next section (see McAlister, 1983, for additional detail), is not unlike the approach used to estimate cross-price elasticities. Cross-price elasticity estimation requires measurement at two points in time with an intervening system shock. One measures demand for product X, changes the price of product Y, then remeasures demand for product X. The change in the demand for X is interpreted via price theory to provide an estimate of Y's competitive impact on X.

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[3]The PRODEGY technique is based upon a criterion called forced switching which requires manipulation of the availability of certain products. In our further discussion of PRODEGY, we employ a different criterion proposed by Urban, Johnson and Hauser (1983) when experimental control of the choice environment is not possible.

[4]Strictly speaking, since the measure we develop is not a ratio of percentage changes, we choose the term response rather than elasticity. However, the measure is conceptually similar to a cross-elasticity using changes in past consumption rather than price changes.

To obtain the cross-consumption response we propose to measure the unconditional probability of consuming product X, allow the consumption of product Y, then measure the conditional probability of consuming X given that Y has been consumed. The difference in the conditional and unconditional consumption probabilities is interpreted via a theory of variety seeking to provide an estimate of Y's competitive impact on X.

Notice that this measurement technique is resistant to the problems Day and Shocker (1976) identified in measuring cross-price elasticities. Regarding their first point, the "shock to the system" is a change in the internal state of the individual who consumed Y instead of a change in Y's price in the marketplace, there will be no competitive reaction clouding the data.

Regarding their second point, the proposed technique yields, as a by-product, an estimate of relative preferences for aspects of relevant brands. Theory relates relative preferences for aspects to competitive interrelationships (McAlister, 1983, see also the "Modeling Framework" section of this paper). A change in product composition would imply a change in the aspect structure of relevant products. To the extent that one knows or can judgmentally estimate the resulting aspect structure of relevant brands and the relative preferences for aspects introduced into the system, the new competitive interrelationships can be estimated without resorting to a complete recalibration.

Finally, regarding their third point for frequently consumed products we have more than enough data to estimate competitive interrelationships at the individual level. Each consumption occasion provides an observation of the impact of one selection on the next.

Modeling Framework

The model we use to describe individual variety seeking behavior and from which we will draw our measure of cross-consumption response is based on four assumptions.

First, we assume that each brand consists of a bundle of want satisfying aspects. The preference for a brand is the sum of the values of its constituent aspects.

Second, we assume that an individual's preferences for the available brands are influenced by that individual's consumption history. In earlier works (McAlister, 1982 and Lattin, 1983) we explored the impact of the entire consumption history on current choice. In the interest of parsimony, we restrict ourselves to consideration of only the most recent previous choice in this model.

Third, we assume that the consumption of a particular aspect will depress preference for that aspect on the subsequent choice occasion. The amount by which consumed aspects are depressed depends upon the individual's desire for variety. High intensity variety seekers will almost completely discount recently consumed aspects. Low intensity variety seekers will discount recently consumed aspects very little.

Fourth, we assume that the probability that an individual consumes a particular brand on a particular consumption occasion is proportional to the individual's current relative preferences for that brand (see Luce, 1959).

Simply stated, the model holds that the selection on one choice occasion affects preferences on the next choice occasion. Having just consumed a particular "bundle of aspects" (i.e., a brand), variety seekers are less attracted to those aspects when making their next choice so that brands composed of different aspects become relatively more attractive. The

consumer chooses among the brands with probabilities proportional to current relative preferences.

Consider the product class depicted in the Venn diagram in Figure 1. Each circle (or crescent in the case of brand B_6) represents a brand as viewed by an individual. The size of the circle is proportional to the individual's total preference for the brand. Regions of overlap indicate aspects shared by the brands. The size of the overlap indicates the relative preference contributed by the aspect which those brands share. (Notice that brands B_3, B_4, and B_5 have identical composition and that brand B_6 consists of only those aspects of B_2 not possessed by B_1.)

[FIGURE 1 ABOUT HERE]

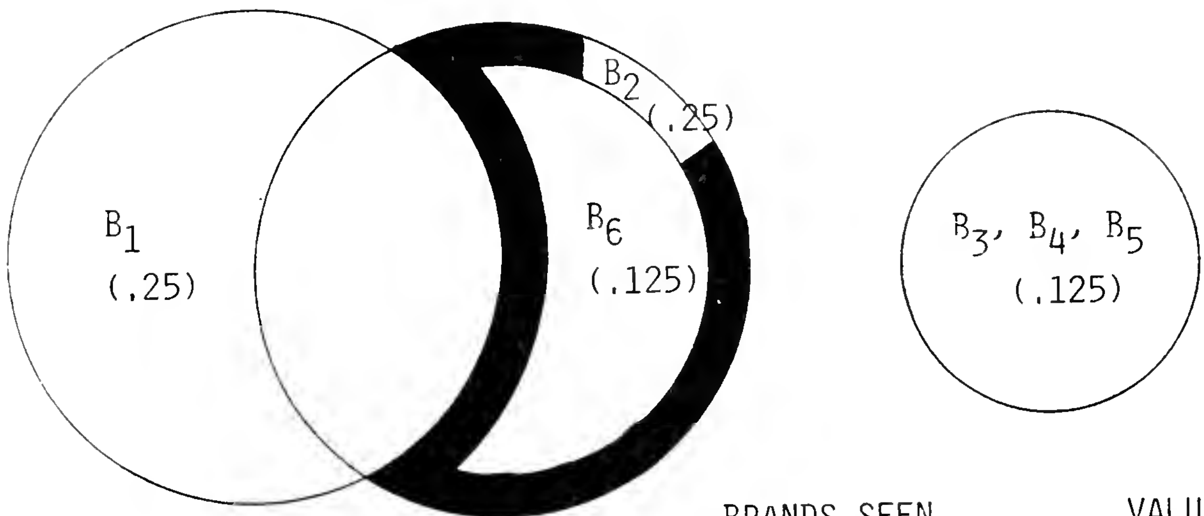
After the individual consumes a brand, say B_2, preference for the aspects provided by B_2 is depressed. The particular amount by which preference is depressed depends on the intensity of the individual's desire for variety. A very high intensity variety seeker might be completely uninterested in any aspects recently consumed. In this case, preference for recently consumed aspects would be depressed to zero. A very low intensity variety seeker's preferences for these recently consumed aspects, on the other hand, would be virtually unaffected.

Net Complements and Substitutes

Scaling Figure 1 so that the sum of the areas of the six circles equals one, we can interpret the size of a brand's circle as the unconditional probability that the individual will choose that brand. Consider an individual who is a moderate variety seeker (i.e., who values recently consumed aspects at only half their original value). The consumption of

FIGURE 1:

VENN DIAGRAM OF MARKET COMPOSITION
FOR A HYPOTHETICAL EXAMPLE



BRAND	PREFERENCE FOR BRAND
B_1	.25
B_2	.25
B_3	.125
B_4	.125
B_5	.125
B_6	.125

BRANDS SEEN AS SHARING AN ASPECT	VALUE OF SHARED ASPECT
B_1 and B_2	.125
B_2 and B_6	.125
B_3 and B_4	.125
B_3 and B_5	.125
B_4 and B_5	.125

We could only approximately represent the π_i's and S_{ij}'s with circles and crescents. The scale is sometimes slightly inaccurate. Also we were forced to draw in some regions which do not correspond to valued aspects. Such regions are shaded. These caveats apply to all Venn Diagrams of market Composition

B_2, for example, would have the following substitution effects within the category. Conditional preference for B_2 would be half the value of its unconditional preference. Conditional preference for B_6 would also be only half its unconditional preference since all the value provided by B_6 is provided by B_2. Finally, conditional preference for B_1 would be less than its unconditional preference since the aspect provided by both B_1 and B_2 is reduced in value. Notice that B_3, B_4 and B_5 - brands that share no aspects with B_2 and hence cannot be substituted for by B_2 - would experience no reduction in preference.

The complementary effect of B_2 on the other brands is captured in the rescaling of conditional preferences into probabilities. Unconditional aspect preferences (aspect preferences before B_2 was consumed) were scaled to sum to one. The substitution effect of B_2 on B_1, B_2 and B_6 led to a reduction in conditional preference for those brands. These conditional preferences sum to something less than one. We obtain the <u>relative</u> conditional preferences (and hence the conditional choice probabilities) by scaling all conditional preferences so that they sum to one.

In sum, B_2 has a substitution effect on all brands with which it shares valued aspects. Further, B_2 has a complementary effect on <u>all</u> brands. It is the net of these two effects in which we are interested.

We can say unequivocally that B_2 has a complementary effect on brands chosen by the individual with which it shares no valued aspects. Those brands are serving different components of the composite need than B_2 serves. No such unequivocal statement can be made for those brands which share some valued aspect with B_2.

Consider B_2's net effect on B_1. Conditional preference for that apsect which they share is depressed by B_2's substitution effect.

However, the aspect unique to B_1 has become relatively more attractive due to B_2's complementary effect. For this particular example, the two effects almost exactly cancel. Consumption of B_2 has no net effect on the probability of consuming B_1. B_1 is independent of B_2.

B_6, on the other hand, experiences a net substitution effect given the consumption of B_2. The dramatic reduction of B_6's conditional preference due to B_2's substitution effect is somewhat moderated by B_2's complementary effect. Still, the net effect is a reduction in the conditional probability of consuming B_6.

Figure 2 illustrates the relative conditional preferences that result following the consumption of B_2. Not suprisingly, B_2 and B_6 shrink noticeably in area. B_3, B_4 and B_5 experience no reduction in conditional preference and their relative conditional preference is inflated by the rescaling. The area of B_1 remains virtually unchanged. The composition of that area, however, does change. The aspect shared with B_2 has been depressed and B_1's unique aspect has been inflated.

[FIGURE 2 ABOUT HERE]

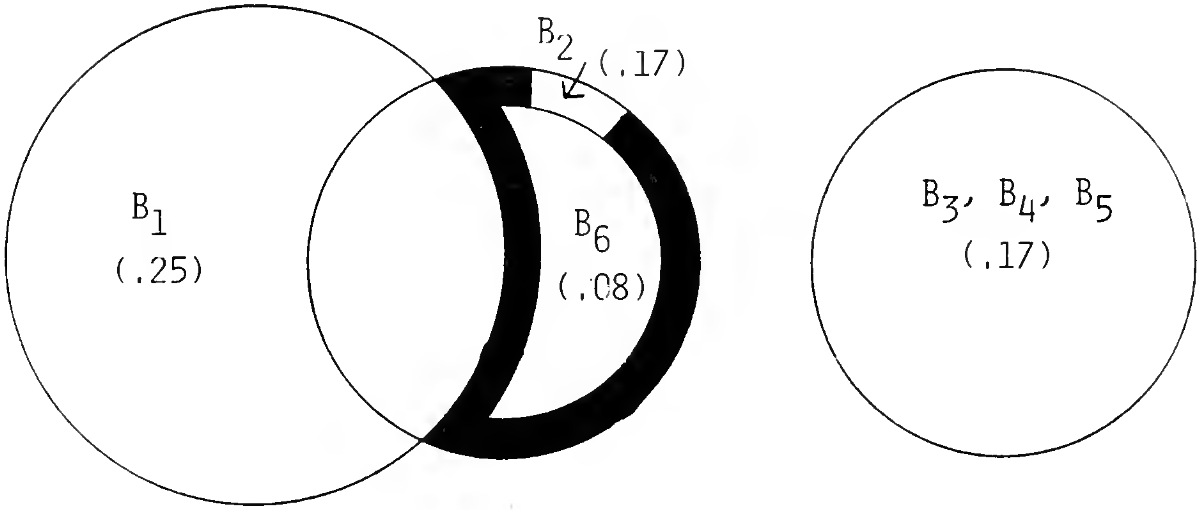
We cannot say anything about the competitive relationships between brands not chosen by the consumer. We will assume that all brands outside the consumer's choice set exhibit competitive independence from those brands within the consumer's choice set.

<u>Analytical Statement of the Model</u>

To describe the model analytically, we let π_j be the area of the circle corresponding to brand B_j before any choices have been made. Thus, π_j corresponds to the individual's unconditional preference for brand j. These π_j's are scaled so that $\sum_j \pi_j = 1$. We denote the area

FIGURE 2:

VENN DIAGRAM OF MARKET COMPOSITION FOR HYPOTHETICAL EXAMPLE CONDITIONAL ON HAVING JUST CONSUMED B_2



BRAND	CONDITIONAL PREFERENCE FOR BRAND	BRANDS SEEN AS SHARING AN ASPECT	CONDITIONAL VALUE OF SHARED ASP
B_1	.25	B_1 and B_2	.09
B_2	.17	B_2 and B_6	.08
B_3	.17	B_3 and B_4	.17
B_4	.17	B_3 and B_5	.17
B_5	.17	B_4 and B_5	.17
B_6	.08		

of the intersection of B_i and B_j by S_{ij}. Thus S_{ij} corresponds to the individual's preference for the aspect common to B_i and B_j. Finally, we denote the discount factor for recent consumption by V. Thus, V corresponds to the intensity of the individual's desire for variety. $V = 0$ indicates no desire for variety. $V = 1$ indicates the highest desire.

An individual's conditional preference for B_i given that she or he most recently consumed B_j is $\pi_i - VS_{ij}$, the unconditional preference for B_i minus some fraction of the value provided by B_i and B_j. These conditional preferences must be rescaled following the consumption of B_j. Thus, the relative conditional probability of consuming B_i given that B_j was just consumed is

$$P_{i|j} = \frac{\pi_i - VS_{ij}}{\sum_k (\pi_k - VS_{kj})}$$

To present a Venn diagram of the individual's view of the market, we need to know the values of π_i and S_{ij} for all brands. We can estimate these parameters using a linear program to minimize the sum of the absolute differences between the theoretical values $P_{i|j}$ and the observed first-order transition probabilities.[5] Within this paradigm, we impose the following structural constraints: $\sum_j \pi_j = 1$ (a scaling constraint), $\sum_{k \neq j} S_{kj} \leq \pi_j$ (the value provided by aspects of B shared with other brands cannot exceed the total value of B_j), and $\pi_j \geq 0$, $S_{ij} \geq 0$ (non-negativity constraints).

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[5]In order to achieve linearity, we specify V a priori and solve the problem. We then search over values of V in order to find the best estimates of π_i and S_{ij}. See McAlister (1983) for details on the structure of the program.

Cross-Consumption Response

Having estimated the model, we can obtain a measure of the net change in demand for B_i induced by the recent consumption of B_j. π_i represents the unconditional preference for B_i. $P_{i|j}$ represents the relative conditional preference for B_i following the consumption of B_j. The quantity $P_{i|j} - \pi_j$ defines our measure of cross-consumption response. It represents the net change in preference for B_i in response to the consumption of B_j. This measure of cross-consumption response describes a continuum of substitute and complementary relationships. If $P_{i|j} - \pi_i < 0$ (the consumption of B_j lowers the probability of choosing B_i), then B_j is a net substitute for B_i. The more negative this number, the closer a substitute B_j is for B_i. If $P_{i|j} - \pi_i > 0$ (the consumption of B_j increases the probability of choosing B_i), then B_j is a net complement to B_i. The more positive this number, the more powerful a complement B_j is to B_i.

It is interesting to examine the conditions under which $P_{i|j} - \pi_i$ achieves a positive or negative sign. In particular, B_j will be a net substitute for B_i (i.e., $P_{i|j} - \pi_i < 0$) if and only if $\pi_i < S_{ij}/\sum_k S_{kj}$. Thus, if B_i shares more than a proportional amount of its want satisfying value with B_j, B_j is a net substitute for B_i. The greater the preference for aspect shared by B_i and B_j relative to the preference for aspects B_j shares with all relevant alternatives, the greater the net substitutability of B_j for B_i. Similarly, if B_i shares less than a proportional amount of its want satisfying value with B_j (i.e., $\pi_i > S_{ij}/\sum_k S_{kj}$), then these conditions are equivalent to saying that B_j is a net complement to B_i.

We can use the cross-consumption response measure to indicate net substitute and complementary relationships at the aggregate level. In

particular, if the weighted average of $P_{i|j} - \pi_i$ across individuals is less than zero, we can say that in the aggregate B_j is viewed as a net substitute for B_i. With a large enough sample of individuals it may also be possible to examine the views of different user segments. Our objective is not only to identify those interrelationships which show at the aggregate level, but also to bring to light relationships which exist at a segment level and are masked in aggregation.

Representations

Goals

We seek a representation of cross-consumption response which will display the competitive interrelationships among products. At the same time, we wish to preserve all the information provided by the cross-consumption response measure. In particular, we want a representation that will preserve the asymmetry inherent in the relationships between products, reflect the entire continuum of relationship intensity, and contrast substitutability and complementarity.

Existing representations of competitive interrelationships among products do not meet these requirements. Simple market partitions reduce the continuum of competitive intensity to a dichotomy: either two products are classified in the same partition, (and hence as being substitutes), or they are not (hence, independent). Hierarchical structures permit some gradation of the intensity of the relationship, but cannot reflect complementarity between products. Perceptual maps, embedded in Euclidean space, imply a symmetric relationship between each pair of products. The Venn diagrams shown in Figures 1 and 2 display the distribution and value of want satisfying characteristics among products in the product class.

However, one cannot directly read the net substitution or complementary effect from such figures.

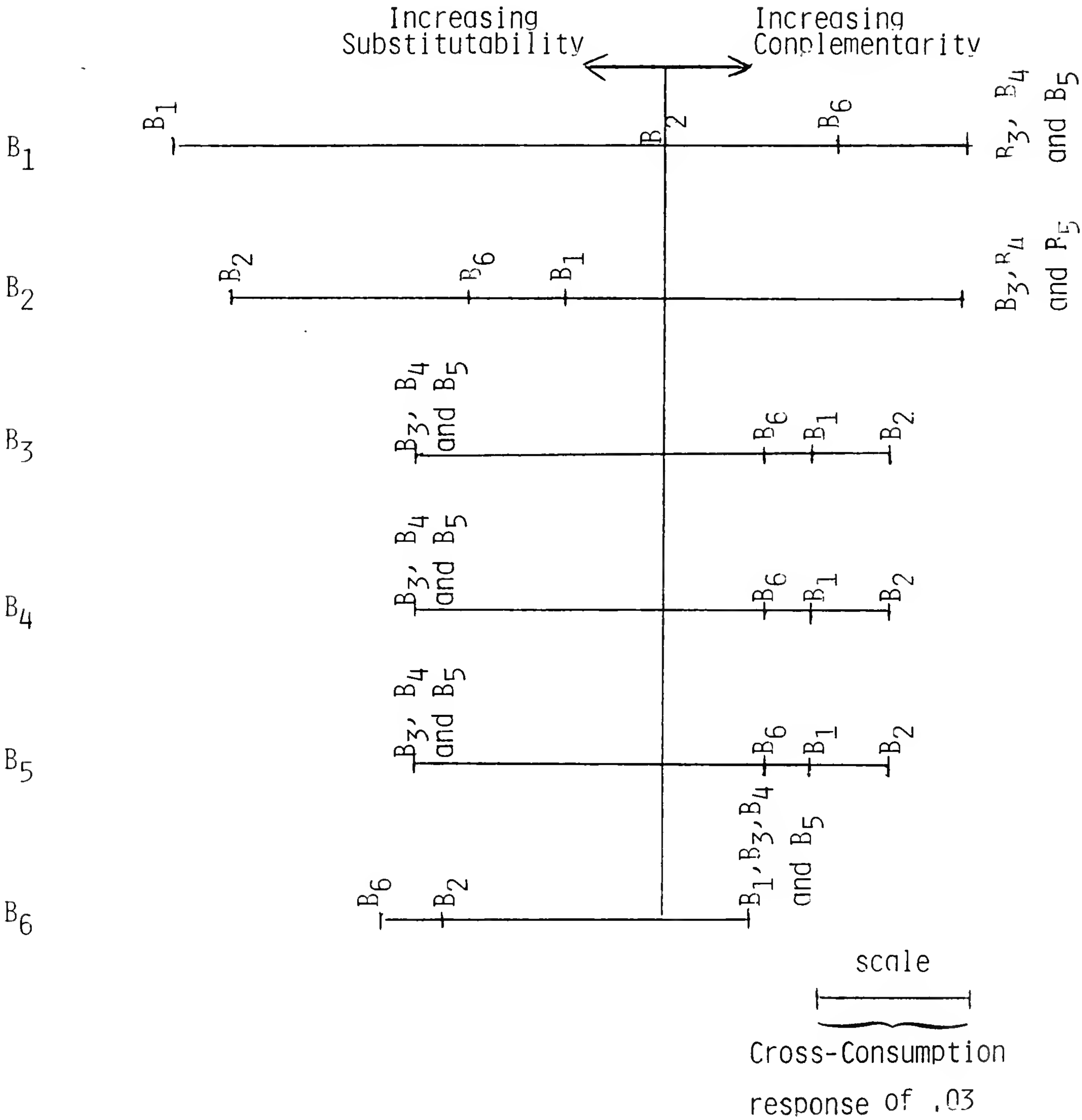
We suggest a separate representation for each brand. In each brand-specific representation, we picture the cross-consumption response of the brand to the consumption of each of the other relevant brands. Thus, the brand specific representation for B_i is simply a continuum in which net complementary brands (with $P_{i|j} - \pi_i > 0$) are placed to the right and net substitutes (with $P_{i|j} - \pi_i < 0$) are placed to the left. The continuum is a "brand's-eye-view" of the impact of the other relevant brands on the brand in question. Our overall representation is just the vertical "stacking" of each of the brand-specific continua. Though not as parsimonious as existing representations, these "brand's-eye-views" satisfy our requirements of preserving asymmetry, continuity and contrast between substitutability and complementarity.

[FIGURE 3 ABOUT HERE]

Figure 3 illustrates this representation for the hypothetical example presented in Figures 1 and 2. The upper most bar in this graph represents B_1's-eye-view of the market. The location of the brands along B_1's continuum indicate the cross-consumption response of B_1 to each of the brands. Brands B_3, B_4 and B_5 are strong net complements to B_1. This makes sense when one examines Figure 1. Brands B_3, B_4 and B_5 share no aspect with B_1. They address a different component in the consumer's composite need. B_6 is also a net complement. Again, this arises because B_6 shares no aspect with B_1.

FIGURE 3:

BRAND'S-EYE-VIEWS OF CROSS-CONSUMPTION RESPONSE FOR HYPOTHETICAL EXAMPLE



B_2 is neither a net substitute nor a net complement to B_1. As was explained earlier, the consumption of B_2 depresses relative conditional preference for the aspect B_1 shares with B_2. This depression is almost exactly compensated by the enhanced relative conditional preference for B_1's unique aspect. On balance, the consumption of B_2 doesn't effect the subsequent probability of consuming B_1.

Finally, we have B_1 located on the extreme left end of its own continuum. Not suprisingly, B_1 is its own best substitute. Notice that this effect holds for all brands. In each brand's-eye-view, the extreme left end of the continuum is anchored by that brand itself. (B_3, B_4 and B_5 are perfect substitutes - they provide exactly the same aspect - and hence jointly anchor the left ends of their brand's-eye-views.) This phenomenon will be repeated in the empirical example to follow and is a consequence of the theory.[6]

The second line in the graph in Figure 3 is B_2's-eye-view of the market. Brands B_3, B_4 and B_5 are net complements for B_2. They share no aspect with B_2. Brands B_1 and B_6 are net substitutes for B_2. Through an aspect shared with B_2, B_1 or B_6 provides enough of what B_2 might offer to make B_2, on balance, less preferred after the consumption of B_1 or B_6. Examining the next three bars in Figure 3, we see that B_1, B_2 and B_6 complement B_3, B_4 and B_5 and that B_3, B_4 and that B_5 substitute for one another, as mentioned above. The last

[6]The particular assumption of the theory which drives this result is that $V \geq 0$. $V < 0$ would indicate a learning effect: consumption of the brand at one point in time would increase the probability of subsequent consumption of that brand. Such behavior would lead to a Markov transition matrix with large diagonal entries and small off-diagonal entries. The data used in this study did not exhibit this property. See McAlister (1983) for explanation of the degradation in fit when V was allowed to take negative values.

bar in the graph indicates that B_1, B_3, B_4 and B_5 complement B_6. B_2 substitutes for B_6 and B_6 is a perfect substitute for itself.

The changes in relative preference between Figure 1 and Figure 2 are reflected in Figure 3. These changes capture the impact of the consumption of brand B_2 on all other brands. These changes determine B_2's position on each of theother brand's-eye-view continuua. That B_1's total area is unchanged from Figure 1 to Figure 2 is reflected in B_2's position at 0 on B_1's brand's-eye-view. B_3's, B_4's and B_5's noticable growth between Figure 1 and Figure 2 is reflected in B_2's position along the net substitute continuua for those brand's-eye-views.

One final thing to notice is that a brand is more likely to experience net complementary effects from other brands than net substitute effects. Intuitively, this follows from the fact that variety-seekers have several components to their composite need. The array of brands in their consumption sets meet, to some extent, these diverse desires. Hence, we have complementarity. Mathematically total net substitute effects must balance total net complement effects.[7] Because each brand is a perfect substitute for itself, the effect of the remaining brands must be, on balance, complementary.

Application of the Approach

Data

We demonstrate our approach using data on individuals' consumption of

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[7]Here we are simply saying that since unconditional probabilities sum to one and conditional probabilities sum to one, the differences between conditional and unconditional probabilities must sum to zero. Positive differences between conditional and unconditional probabilities indicate complements. Negative differences between conditional and unconditional probabilities indicate substitutes.

soft drinks. The data were collected from October through December, 1978.[8] The subjects were 36 graduate and undergraduate students enrolled in the Schools of Business Administraton at the University of Washington. Twenty-two percent of the subjects were females.

No economic incentive was offered for participation in the study. Motivation for accurate reporting was provided by having the professor in a bi-weekly class begin each period by distributing data collection forms and requesting that serious thought be given to the task. At each data collection opportunity subjects were asked to report all soft drinks consumed since their last report.

Over the 81 days of the study, 29 students provided enough data to permit estimation of the model described above. These subjects consumed a collective total of 831 soft drinks yielding the aggregate choice shares among the 10 soft drinks or soft drink categories displayed in Table 1.

[TABLE 1 ABOUT HERE]

Aggregate Analysis

Examination of the soft drink data suggests that most individuals consume either diet or non-diet beverages. Over 60% of the subjects (18 out of 29) consume only one of the two types of beverage. Thus, it appears that the different sets of want satisfying characteristics provided by diet and non-diet drinks are neither net substitutes for nor net complements to one another.

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[8]This data was originally collected for a different study reported in McAlister (1982).

For the majority of subjects, diet and non-diet drinks form separate classes which are competitively independent of one another.

The data also suggest that an individual is liable to consume both cola and non-cola beverages. Approximately 70% of the subjects (20 out of 29) consume beverages from both categories. Individuals may be switching between categories (cola and non-cola) in order to achieve a suitable balance in their consumption. To the extent that the consumption of cola stimulates the subsequent consumption of a non-cola (and vice-versa), the two groups of brands can be thought of as complementary.

We have argued that identifying and understanding complementarity between products is a fundamental step in gaining insight about a product class in which variety seeking behavior is an important determinant of consumer choice. Few of the existing techniques for examining competitive interrelationships, as we have said, are equipped to identify and represent this complementarity. Most employ representations (such as market partitions and hierarchical structures) that are too simple to reflect complementarity and substitutability simultaneously.

None of the behavioral techniques based upon brand switching explicitly addresses the notion of complementarity[9]. While all should be able to identify diet drinks and non-diet drinks as independent competitive classes, none should be able to reveal the hypothesized complementarity between colas and non-colas. We investigate these conjectures by applying three of the existing behavioral techniques to the soft drink data: the "empirical" approach to the Hendry method proposed by Kalwani and Morrison (1977), a hierarchical clustering approach proposed by Rao and Sabavala (1981), and

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[9]A possible exception is Zahorik (1983), who separates switching for the sake of variety from competitive switching. However, Zahorik's technique only examines the interrelationships revealed by the competitive switching.

TABLE 1: AGGREGATE CHOICE SHARES

FOR THE 29 SUBJECTS*

Soft Drink	Choice Share
Coke	.32
Diet Pepsi	.10
Dr. Pepper	.06
Pepsi	.11
7-Up	.13
Tab	.07
Cola	.03
Diet Cola	.04
Fruit Flavor	.10
Diet Fruit Flavor	.03

*The compositions of the last four categories is as follows. COLA: RC, Cola, Mr. Pibb. DIET COLA: Diet Cherry Cola, Diet Cola, Pepsi Light. FRUIT FLAVOR: Mountain Dew, Sprite, Fresca, Gatorade, Ginger Ale, Grape, Grapefruit Drink, Orange, Quench, Rootbeer, Squirt, Strawberry. DIET FRUIT FLAVOR: Sugar-free 7-Up, Diet Creme Soda, Diet Lemon-Lime, Diet Orange, Diet Raspberry, Diet Rootbeer.

the PRODEGY technique of Urban, Johnson and Hauser (1983). We then present our "brand's-eye-view" representation of cross-consumption response.

Alternative Techniques

"Empirical" Hendry"[10]. The fundamental assertion of the Hendry market partitioning methodology is that switching between competitive products will be proportional to the product of aggregate choice shares; i.e.,

$$E_{ij} = K_w m_i^A m_j^A \qquad \text{for } i \neq j$$

where E_{ij} is the expected switching between products i and j, m_i^A and m_j^A are the aggregate choice shares of brands i and j, respectively, and K_w is a switching constant. A brand-primary partition (i.e., no structure) requires only one switching constant, while a form-primary partition (i.e., several groups of brands clustered together according to the form of the product) requires a switching constant for each form plus a single constant to describe the switching among forms.

Kalwani and Morrison (1977, p. 476) suggest the following approach to Hendry:

"1. Set up a hypothesis about the nature of partitioning in the market....

2. Analyze the actual switching behavior by calculating empirically the values of the switching constant both across and within partitions...."

---

[10]Rubinson, Vanhonacker and Bass (1980) present a theoretical approach to Hendry which they constrast to the empirical approach proposed by Kalwani and Morrison. They contend that the theoretical approach provides more than simply a "parsimonious description" of consumer switching, and that it affords an assessment of a mixed brand-form structure that the empirical approach does not. We choose the empirical approach because we do not consider the mixed brand-form structure and because the fits given by the empirical approach dominate those provided by the theoretical approach.

The partition that best fits the observed patterns of switching in the data is the best Hendry representation of the competitive market structure.

The results of our empirical Hendry analysis of the soft drink data are shown in Figure 4. We proposed three market partitions: a brand-primary structure, a form-primary structure of diet and non-diet forms, and another form-primary structure of diet cola, diet non-cola, cola, and non-cola forms. We used as a measure of fit the sum of squares of actual minus fitted switching, i.e.,

$$SS = \sum_{i \neq j} (N_{ij} - NK_w m_i^A m_j^A)^2$$

Where N_{ij} is the aggregate of actual switches from brand i to brand j, N is the aggregate total number of switches and SS is the total sum of squares.

[FIGURE 4 ABOUT HERE]

The form-primary structure for diet/non-diet drinks is the best Hendry representation of product competition. The fit improves from SS = 1901 for the brand-primary structure to SS = 1385. The switching constants indicate that much more switching occurs within each form (.505, .567) than between forms (.230). Hendry also suggests that no further distinction can be made within the diet and non-diet classes. The second form-primary structure, in which we separate colas from non-colas, has a worse fit than the brand-primary structure (SS = 2168 vs. SS = 1901 for brand-primary).[11]

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[11] A chi-square measure, traditionally used to assess the fit of proposed partitions,does not clearly demonstrate the superiority of the diet/non-diet structure over the brand-primary structure. The latter systematically over predicts switching between diet and non-diet beverages. But because the relatively large predicted values appear in the denominator of the chi-square measure, the squared deviations terms are diminished. Thus, the brand-primary and diet/non-diet structures exhibit similar chi-square measures (329.7 and 336.7 respectively) despite very different sum of squares terms.

<u>Hierarchical Clustering</u>. Rao and Sabavala (1981) contend that a relatively high level of switching between products is indicative of competition between the two. They propose a hierarchical technique for clustering products together according to the "flow" of switching between them.[12] F_{ji}, the flow switching from j to i, is given by

$$F_{ji} = \frac{R^A_{i|j}}{m^A_i}$$

where $R^A_{i|j}$ is the observed aggregate probability of choosing brand i following a choice of brand j, and m^A_i is the aggregate choice share of brand i.

Since F_{ji} is a ratio of actual switching to expected switching (under an aggregate zero order model), it is interpretable as an empirical estimate of the pairwise switching constant between brands i and j. The hierarchical technique clusters brands so that all pairs of products within a competitive subclass exhibit high switching constants. Under this criterion, so similar to that of "Empirical" Hendry, it is not surprising that the tree structure for the soft drink data (shown in Figure 5) captures the competitive distinction between diet and non-diet beverages. The low flows of switching across competitive sub subclasses are attributable to the fact that few subjects consumed both diet and non-diet drinks.

[FIGURE 5 ABOUT HERE]

Figure 5 is the result of a cluster routine. Those brands joined together at the lowest point in the figure are those between which the flow of switching is highest. As one proceeds up the figure, links represent successively lower levels

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[12] Rao and Sabavala suggest the use of either the upper or lower diagonal of the flow matrix. We present results based upon the upper diagonal, although both upper and lower diagonals yield similar clustering structures.

FIGURE 4:

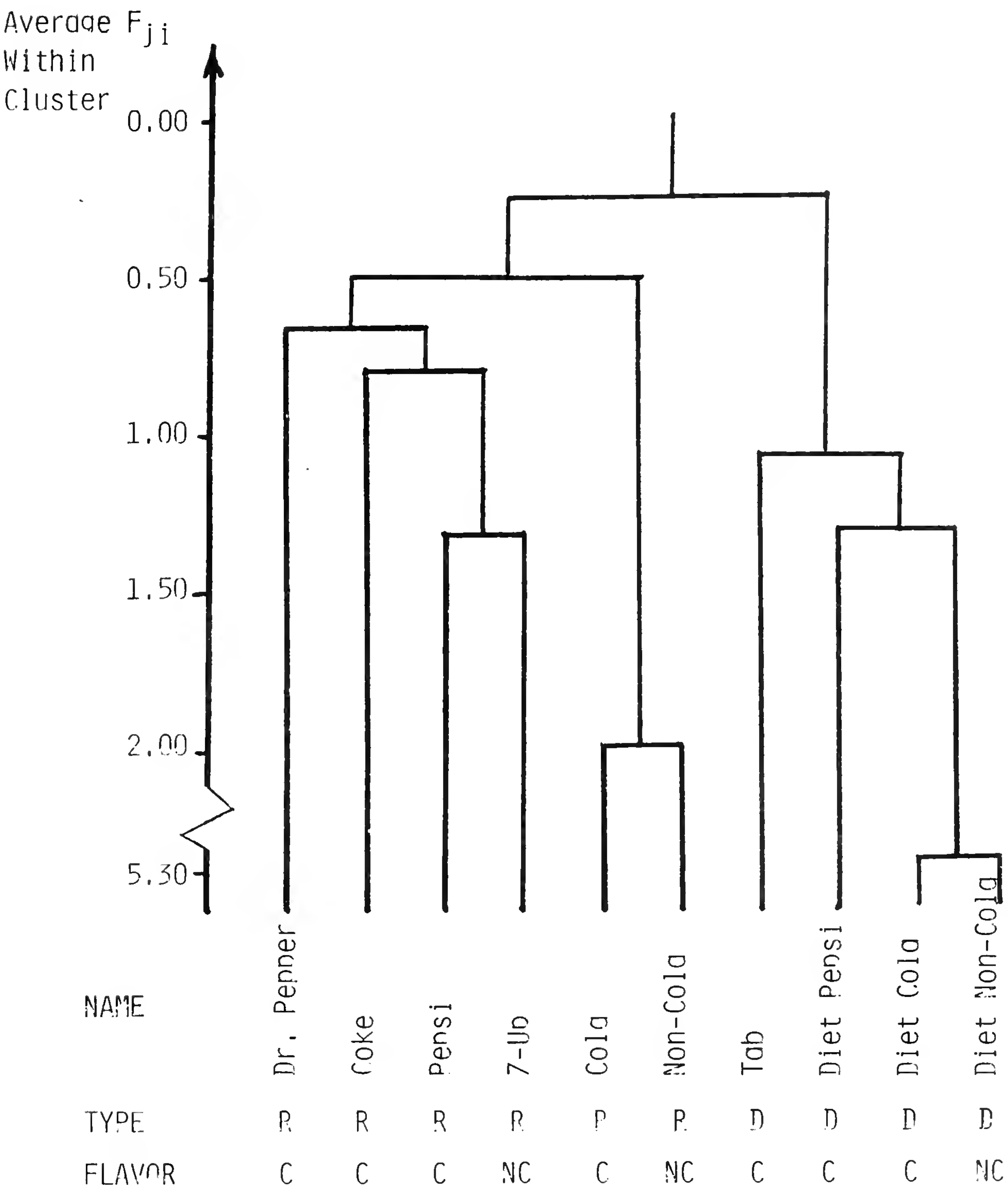
RESULTS OF EVALUATING THREE PROPOSED MARKET PARTITIONS USING THE EMPIRICAL APPROACH TO HENDRY PROPOSED BY KALWANI AND MORRISON (1977)

PROPOSED STRUCTURE	ESTIMATED SWITCHING CONSTANTS	FIT
1.) Brand Primary		SS = 1901.3
Across brands	K_W = .555	
2.) Form Primary		SS = 1385.1
Across forms	K_W = .230	
Within form 1: Diet	K_1 = .505	
Within form 2: Non-Diet	K_2 = .567	
3.) Form Primary		SS = 2168.1
Across forms	K_W = .505	
Within form 1: Diet Cola	K_1 = .305	
Within form 2: Diet Non-Cola*	K_2 = .000	
Within form 3: Cola	K_3 = .214	
Within form 4: Non-Cola	K_4 = .406	

* Only one brand within form.

FIGURE 5:

HIERARCHICAL CLUSTERING OF SOFT DRINK STUDY DATA
TECHNIQUE PROPOSED BY RAO AND SABAVALA (1981)
(TYPE: R = REGULAR, D = DIET FLAVOR C = COLA, NC = NON-COLA)



of average flow between clusters. Rao and Sabavala assume that the higher the level of switching (i.e., the lower in the Figure that two brands are linked) the greater the degree of substitutability of the brands. This suggests that the highest levels of substitutability exist between colas and non-colas: Pepsi and 7-Up, Diet Cola and Diet Fruit Flavor, and Cola and Fruit Flavor.

PRODEGY. Urban, Johnson and Hauser (1983) propose to identify sets of competing products using a heuristic of product deletion. In particular, they define a group of products as a competitive product submarket if, following the deletion of one product, consumers of the deleted product are more likely to choose again within the group than would be predicted by the aggregate choice shares of the remaining products in the group. If we denote the aggregate probability of choosing product i following the deletion of product j by P (j), and the aggregate choice share of products i and j by m_i^A and m_j^A, respectively, then a set of products S form a competitive product submarket if

$$\sum_{i \in S} \quad P_i^A(j) \quad - \quad \frac{m_i^A}{1 - m_j^A}$$

is sufficiently large for all products $j \in S$. Urban, Johnson and Hauser (1983, pp. 8-10) provide a statistical test which can be used to evaluate the adequacy of a proposed submarket structure. Any partition with an overall z-score of 1.96 or above is acceptable at a 95% level of confidence.

When it is not possible to observe $P_i^A(j)$ by direct manipulation of the availability of product j, Urban, Johnson and Hauser (1983, pp. 15-16) suggest several alternative estimates. We consider their estimate of $P_i^A(j)$ based upon individual choice shares. To use this estimate, we must assume that individuals obey

a constant ratio model; i.e., following the deletion of product j, the individual's choice shares for the remaining products increase proportionately. If we denote the choice shares for individual h for products i and j by m_i^h and m_j^h, respectively, then

$$P_i^h(j) = \frac{m_i^h}{1 - m_j^h} ,$$

where $P_i^h(j)$ is the probability that an individual chooses product i following the deletion of product j. We can then estimate $P_i^A(j)$ by

$$\sum_h m_j^h \; P_i^h(j) \quad / \; \sum_h m_j^h$$

We applied the PRODEGY technique to the softdrink data, suggesting three different market partitions: {Cola, Non-Cola}, {Diet, Non-diet}, and {Cola, Non-cola, Diet Cola}.[13] The results are shown below in Figure 6.

[FIGURE 6 ABOUT HERE]

Clearly, the {Cola, Non-cola} partition is not adequate to represent the competition among soft drinks. A z-score of -0.31 indicates that on average, more competition occurs between submarkets than within them. The {Diet, Non-diet} partition nicely captures the competition among diet and among non-diet drinks, with an overall z-score of 2.37 significant at the 95% level. Our effort to further distinguish relationships between cola and non-cola reduces the overall z-score for the partition to 1.4, not significant at the 90% level.

Markov Decomposition Analysis

Total Sample Analysis. As indicted earlier we are able to estimate V^h, π_i^h, S_{ij}^h

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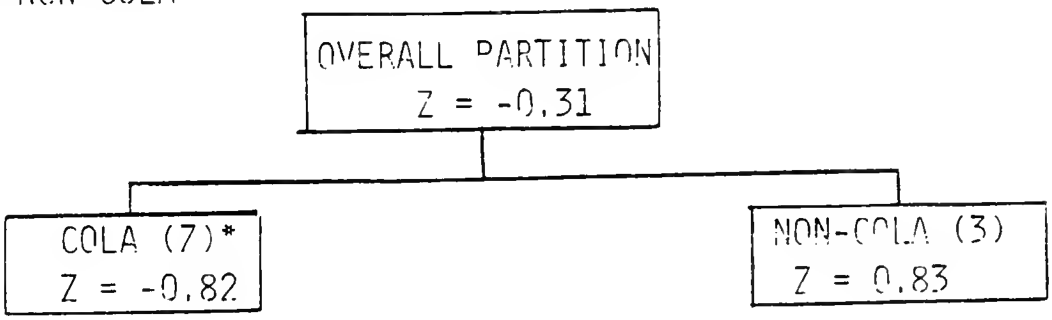
[13] Because PRODEGY is based upon a product deletion heuristic, there is no way to evaluate a submarket consisting of one product. Therefore, we leave Diet Non-cola out of the third proposed partition.

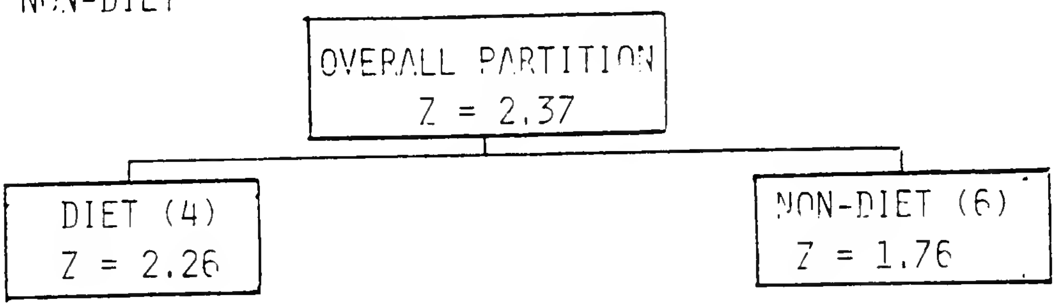
FIGURE 6:

RESULTS OF EVALUATING THREE PROPOSED MARKET PARTITIONS
USING THE PRODEGY TECHNIQUE PROPOSED
BY URBAN, JOHNSON, AND HAUSER (1983)

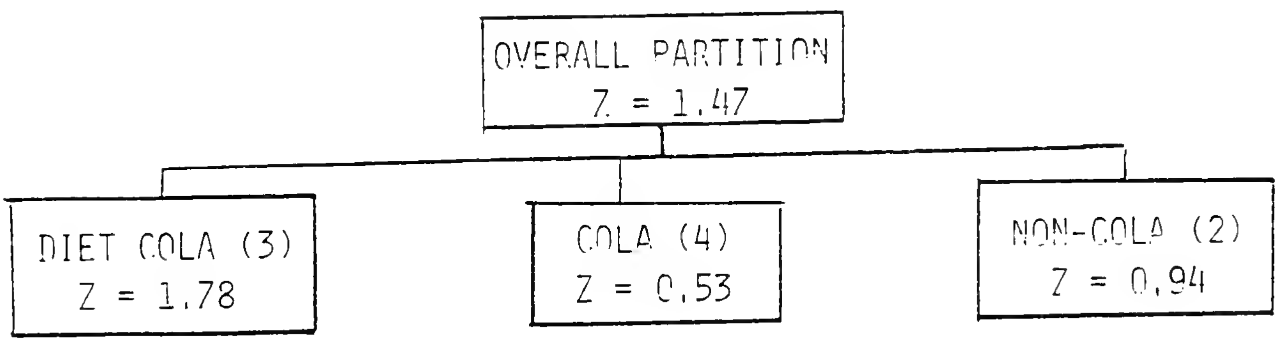
1. COLA, NON-COLA



2. DIET, NON-DIET



3. DIET COLA, COLA, NON-COLA **



*Number in parentheses indicates number of brands in submarket

**Partition includes only nine brands because the tenth brand, Diet Fruit Flavor, would be a single brand category. By definition, there can be no forced switching between brands within a single brand category.

for all brands i and j for consumer h[14] by equating the theoretical conditional consumption probability $P_{i|j}^{h}$ to the empirically observed conditional frequency $\hat{P}_{i|j}^{h}$. As reported in McAlister (1983), individual choice is not typically zero-order among these subjects. An individual making consumption decisions according to a zero-order process would be characterized by a $V = 0$. For the 29 subjects in this study, only 6 display that value. Values of V for other subjects range from .2 to .9 with an average value over the total sample of approximately .4. The values of π_i^h and S_{ij}^h show a similar heterogeniety across subjects.

In order to develop an understanding of aggregate competitive interrelationships, we must aggregate the individual level parameters. Because the heaviness of usage of this product class varied rather dramatically across subjects (from 12 to 62 selections with an average of approximately 35 selections by each subject), we decided to take a weighted average of individual parameters. As weights we use the ratio of the number of choices made by a subject to the total number of choices made. If we let w^h denote the weight reflecting individual h's relative heaviness of consumption, we calculate aggregate parameters as:

$$\pi_i^A = \sum_{h=1}^{29} w^h \pi_i^h \text{ for all brands } i$$

$$S_{ij}^A = \sum_{h=1}^{29} w^h S_{ij}^h \text{ for all brands } i \neq j$$

---

[14]Notice the superscript in which has been added to denote individual h.

These aggregate parameters are used to depict the market as seen by the total sample in the Venn diagram in Figure 7.

To estimate aggregate brand's-eye-views, we could have combined these aggregate π_i^A and S_{ij}^A with a similarly calculated aggregate V. Such an aggregate measure would have lost the impact of the correlation among the π_i^h, S_{ij}^h, and V^h. In order to retain the impact of that correlation we first calculate the individual level cross-consumption response

$$(P_{i|j}^h - \pi_i^h) = \frac{\pi_i^h - V^h S_{ij}^h}{1 - V^h \sum_k S_{kj}^h} - \pi_i^h,$$

and then take a weighted average of those effects yielding the aggregate cross-consumption response

$$(P_{i|j} - \pi_i)^A = \sum_{h=1}^{29} w^h (P_{i|j}^h - \pi_i^h)$$

Recall that $P_{i|j}^h - \pi_i^h < 0$ indicates that brand j is a net substitute for brand i. $P_{i|j}^h - \pi_i^h > 0$ indicates that brand j is a net complement for brand i. $P_{i|j}^h - \pi_i^h = 0$ indicates that the substitute and complement effects of j on i exactly cancel if both brands i and j are chosen by h. $P_{i|j}^h - \pi_i^h$ is also driven to 0 if the consumer does not choose both brands i and j. The subjects in this study chose only an average of 4 of the 10 different brands. Aggregate competitive interrelationships will, therefore, be of smaller magnitude that individual level parameters. Figure 8, the brand's-eye-views of aggregate cross consumption response, bears out this general effect as well as presenting some very interesting information about the market as a whole.

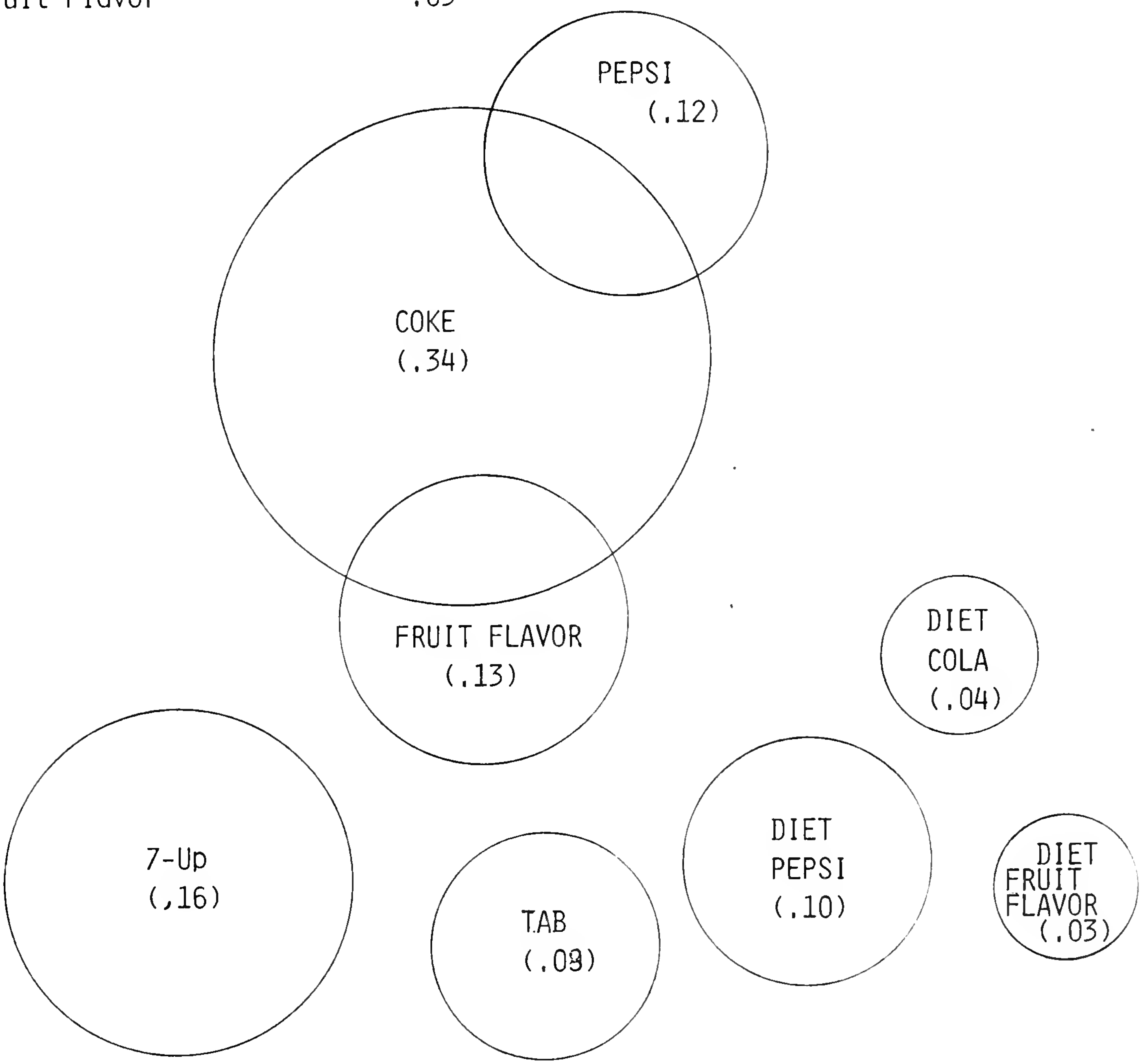
[FIGURE 7 & 8 ABOUT HERE]

FIGURE 7:

VENN DIAGRAM OF MARKET COMPOSITION FOR THE TOTAL EXAMPLE

BRAND	PREFERENCE FOR BRAND* IN TOTAL SAMPLE
Coke	.34
Diet Pepsi	.10
Pepsi	.12
7-Up	.16
Tab	.08
Fruit Flavor	.13
Diet Cola	.04
Diet Fruit Flavor	.03

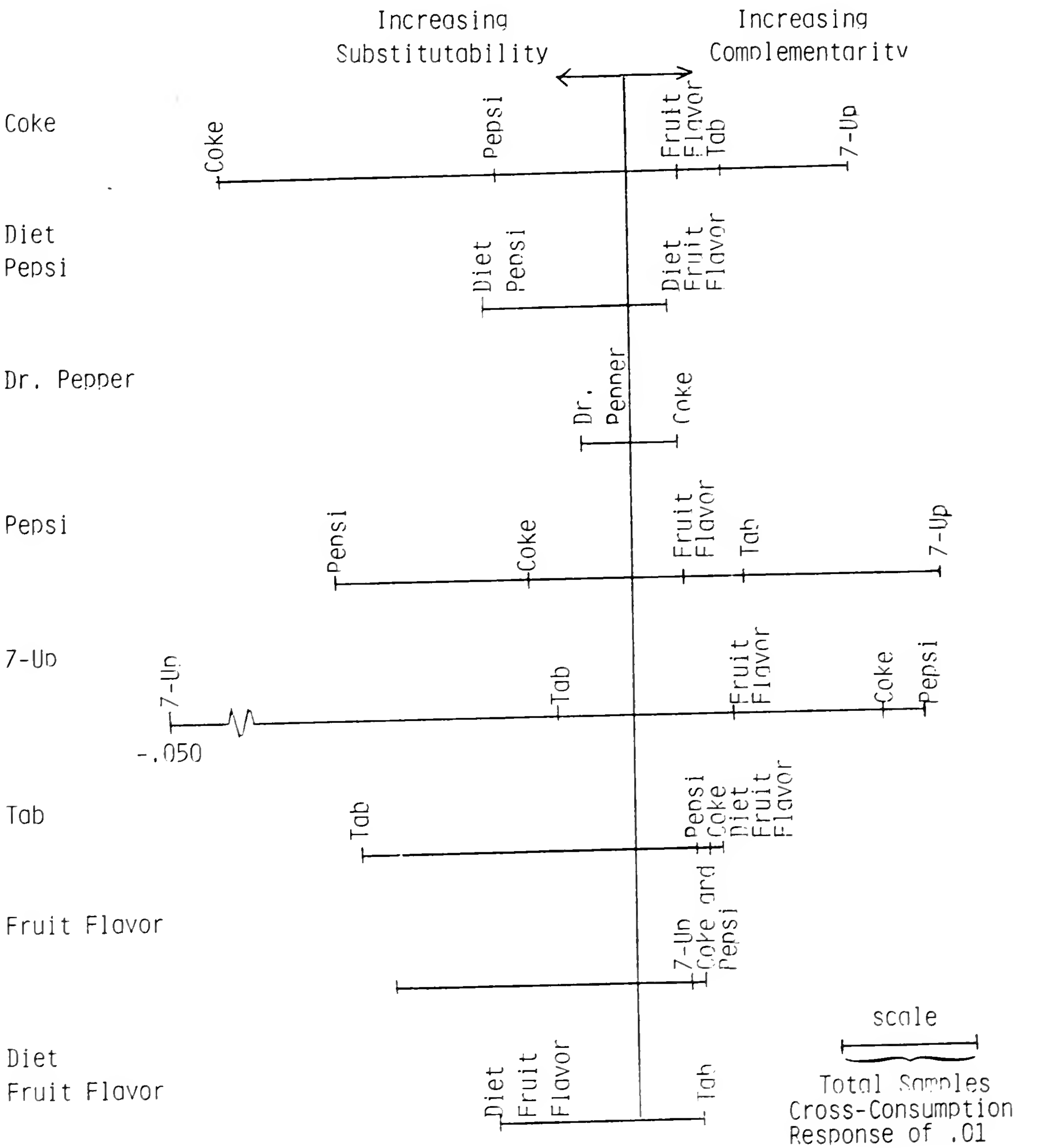
BRANDS SEEN AS SHARING AN ASPECT BY THE TOTAL TAMPLE	ASPECT
Coke and Pepsi	.04
Coke and Fruit Flavor	.04



*The Values displayed in this Figure are those that can be distinguished from zero for $p < .10$.

FIGURE 8:

BRAND'S-EYE-VIEWS OF CROSS-CONSUMPTION RESPONSE BASED UPON THE TOTAL SAMPLE



The first thing to notice in Figure 8 is that our measure of cross-consumption response, like existing techniques, reflects the relative independence of diet drinks from non-diet drinks. It is primarily non-diet drinks that have substitute or complementary effects on other non-diet drinks and primarily diet drinks that have substitute or complementary effects on other diet drinks. Tab, however, is an exception to this rule. In addition to its role among the diet drinks, it also plays a role within the non-diet drinks.

Cross-consumption response also reveals the complementarity between cola drinks and non-cola drinks. Among the diet drinks Tab complements Diet Fruit Flavor and Diet Fruit Flavor complements Tab and Diet Pepsi. Among non-diet drinks the relationship is more subtle. There are, apparently, three classes of non-diet drinks. The first class (call it "major colas") is made up of Coke and Pepsi. The second class (call it "major change of pace") is made up of 7-Up and Tab. The third class (call it "minor change of pace") is made up of the Fruit Flavor and Dr. Pepper. Brands have substitute effects on other brands within their class and complementary effects on brands in the other two classes. Note that although some of the proposed effects are not depicted in Figure 8 none of the documented effects are inconsistent with this scheme. Furthermore, most of the missing effects relate to Dr. Pepper, a small share brand that was only chosen by 3 of the 29 subjects. Dr. Pepper's small share and the small constituency tend to drive its aggregate effect toward zero. Evidence consistent with the grouping of Fruit Flavor and Dr. Pepper is found in the segmentation analyses that follow. Finally, notice that the Cola and Diet-Cola categories do not appear in Figure 8. That is because the only non-negligible effect for those two categories was that of the category as a substitute for itself.

Because we report continuous values for substitute and complementary effects, we are able to compare the magnitude of the effects. Note that Pepsi complements 7-Up more strongly than Coke does; furthermore, 7-Up complements Pepsi more strongly than it does Coke. This more intense complementarity of 7-Up and Pepsi could be exploited in joint promotional efforts, in advertising copy, in shelf pacement of the product, etc. if it appears in analyses of representative market samples.

Consider now Figure 7, the Venn diagram of market composition aggregated across the total sample. Note first that Cola and Dr. Pepper do not appear in the diagram. That is because neither π^A_{Cola} nor $\pi^A_{Dr.\ Pepper}$ were statistically greater than zero for $p > .10$. Similarly notice that there are very few brands whose similarity is statistically greater than zero for $p > .10$. S^A_{ij} can be driven toward zero by subjects who don't consume both i and j or by subjects who consume both i and j but do not i and j as being similar. Hence, S^A_{ij} statistically greater than zero for $p > .10$ requires a fairly widespread perception of nontrivial similarity.

That Coke and Pepsi should exhibit such similarity is not surprising. It is surprising, however, to find a significant similarity between Coke and Fruit Flavor. In the next section we explore that similarity.

Analysis of Segment Perceiving Coke and Fruit Flavor as Similar. For this analysis we select only those six subjects for whom $S^h_{Cola,\ Fruit\ Flavor} > 0$. The subjects' individual level parameters of the six subjects are aggregated in a manner analagous to that just described to aggregate the total sample[15]. Figure 9A in which brands are labeled, shows the Venn Diagram of a ggregate

[15] Because each of the segments is so small, we must forego requirement of statistical significance. With a larger total sample, segment membership should be larger allowing more precise statistical statements.

market composition for this segment. Figure 9B reproduces that structure labeling aspects instead of brands. This double representation is done to facilitate the following exposition.

[FIGURES 9 & 10 ABOUT HERE]

The first thing to notice is that members of this segment have much more homogeneous perceptions of brand similarities than the total sample. (The homogeniety is reflected in larger values for S_{ij}^{A}. A smaller proportion of zeros has been averaged in.) The second thing to notice is that this is a Coke dominated segment. We identify five sources of preference for Coke and label them α_1 through α_5. α_1 is unique to Coke. α_2 is shared with Non-Cola and, in fact, makes up nearly 80% of Non-Cola's value. α_3 is shared with 7-Up. Making up nearly 90% of 7-Up's value. α_4 is shared with Pepsi and make up 100% of Pepsi's value. α_5 is shared with Tab and makes up approximately 40% of Tab's value. Coke provides virtually everything. Only a small amount of want satisfying value is provided by the unique aspects of 7-Up, Non-Cola, Tab, etc.

These effects are reflected in the brand's-eye-views in Figure 10. Almost all brands complement Coke. The aspects they don't share with Coke (α_6 through α_{12}) offer a change of pace to Coke. In particular, Diet Pepsi and Tab substitute for one another as the diet change of pace and Fruit Flavor and Dr. Pepper substitute for one another as the non-diet change of pace.

Notice that Fruit Flavor and Coke both complement Diet Pepsi. This occurs because Coke and Fruit Flavor are large preference brands that share no aspects with Diet Pepsi. However, 7-Up is another large preference brand

that shares no aspects with Diet Pepsi and 7-Up doesn't complement Diet Pepsi. This seeming anomaly is an artifact of aggregation. No subject in this segment chose both 7-Up and Diet Pepsi. Some chose 7-Up. Some chose Diet Pepsi. Hence, both brands are represented on the Venn Diagram. Since they were never chosen together, however, no individual level complementary effects exist to be aggregated. The aggregate Venn diagrams can be misleading in this way. One cannot be sure whether two brands were ever chosen together unless an aggregate similarity measure emerges.

Finally, notice that in Figure 9, as in Figure 7, there is no similarity between 7-Up and Fruit Flavor. A priori, we expected such a similarity to emerge. To gain insight into the market we next investigate the segment of subjects for whom $S_{7\text{-Up, Fruit Flavor}} > 0$.

<u>Analysis of Segment Perceiving 7-Up and Fruit Flavor as Similar</u>. We restrict this analysis to those two subjects for whom $S_{7\text{-Up, Fruit Flavor}} > 0$. Aggregation is performed as before.

[FIGURES 11 AND 12 ABOUT HERE]

The Venn diagram in Figure 11 depicts an intuitively appealing representation of market composition. Coke and Pepsi are very similar. 7-Up and Fruit Flavor are also similar, though less so. The cola drinks share no aspects with the non-cola drinks.

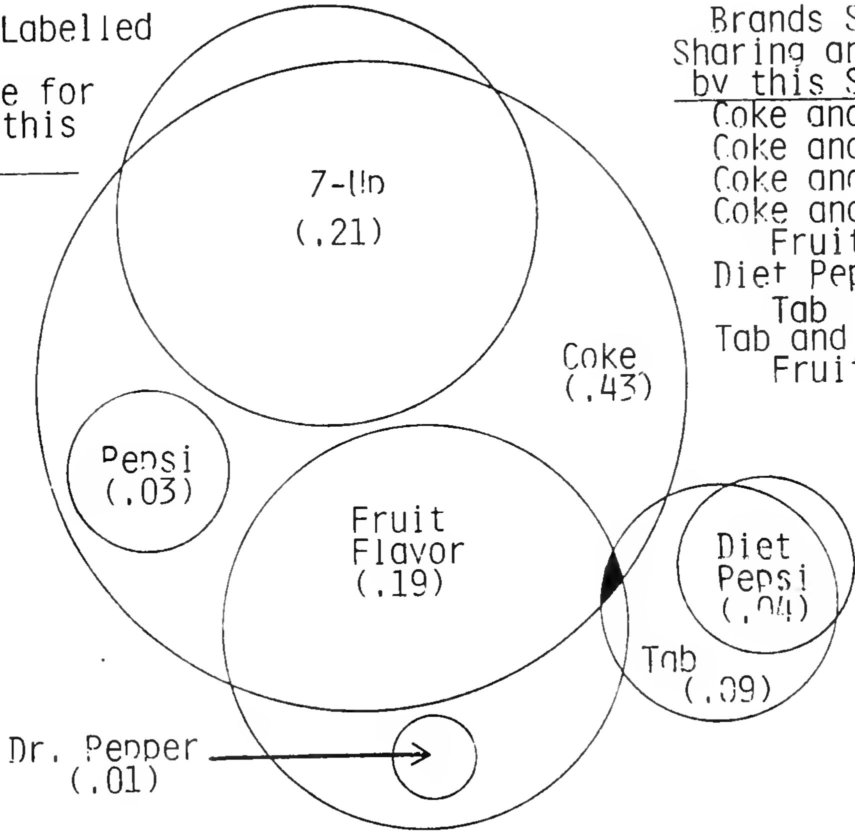
The competitive interrelationships are drawn out in Figure 12. In general, they are consistent with intuition. The one surprising result is the asymmetry of 7-Up and Fruit Flavor's relationship. 7-Up substitutes for Fruit Flavor while Fruit Flavor complements 7-Up. This occurs because 7-Up can provide virtually everything that Fruit Flavor can provide but the

FIGURE 9:

VENN DIAGRAM OF MARKET COMPOSITION FOR THOSE SIX SUBJECTS WHO DRINK BOTH COKE AND FRUIT FLAVOR AND VIEW THEM AS SIMILAR.

Figure 9A: Brands Labelled

rand	Preference for Brand in this Segment
oke	.43
iet Pepsi	.04
r. Pepper	.01
epsi	.03
-Up	.21
ab	.03
ruit Flavor	.18



Brands Seen as Sharing an Aspect by this Segment	Value of Shared Aspect
Coke and Pepsi	.03
Coke and 7-Up	.18
Coke and Tab	.03
Coke and Fruit Flavor	.14
Diet Pepsi and Tab	.03
Tab and Fruit Flavor	.02

Figure 9B: Aspects Labelled

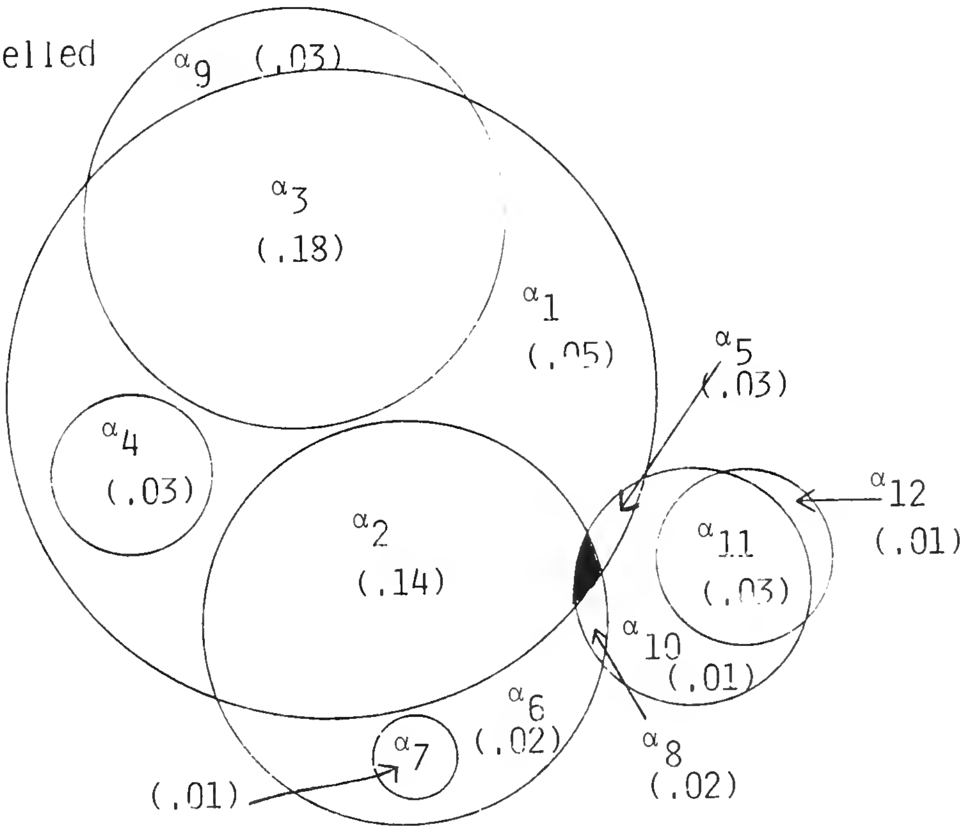


FIGURE 10:

BRAND'S-EYE-VIEWS OF CROSS-CONSUMPTION RESPONSE FOR THOSE SIX SUBJECTS WHO SEE COKE AND FRUIT FLAVOR AS SIMILAR

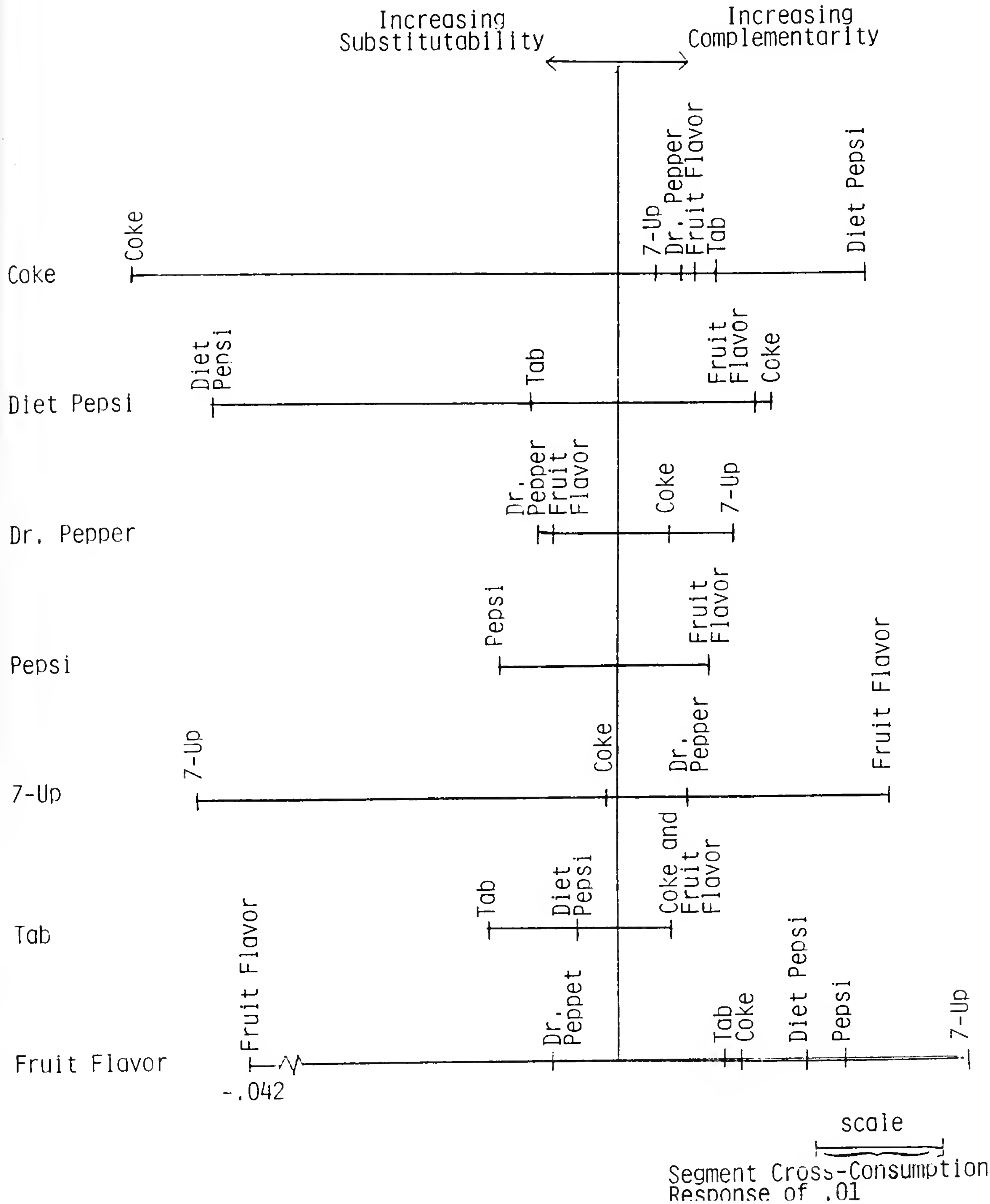
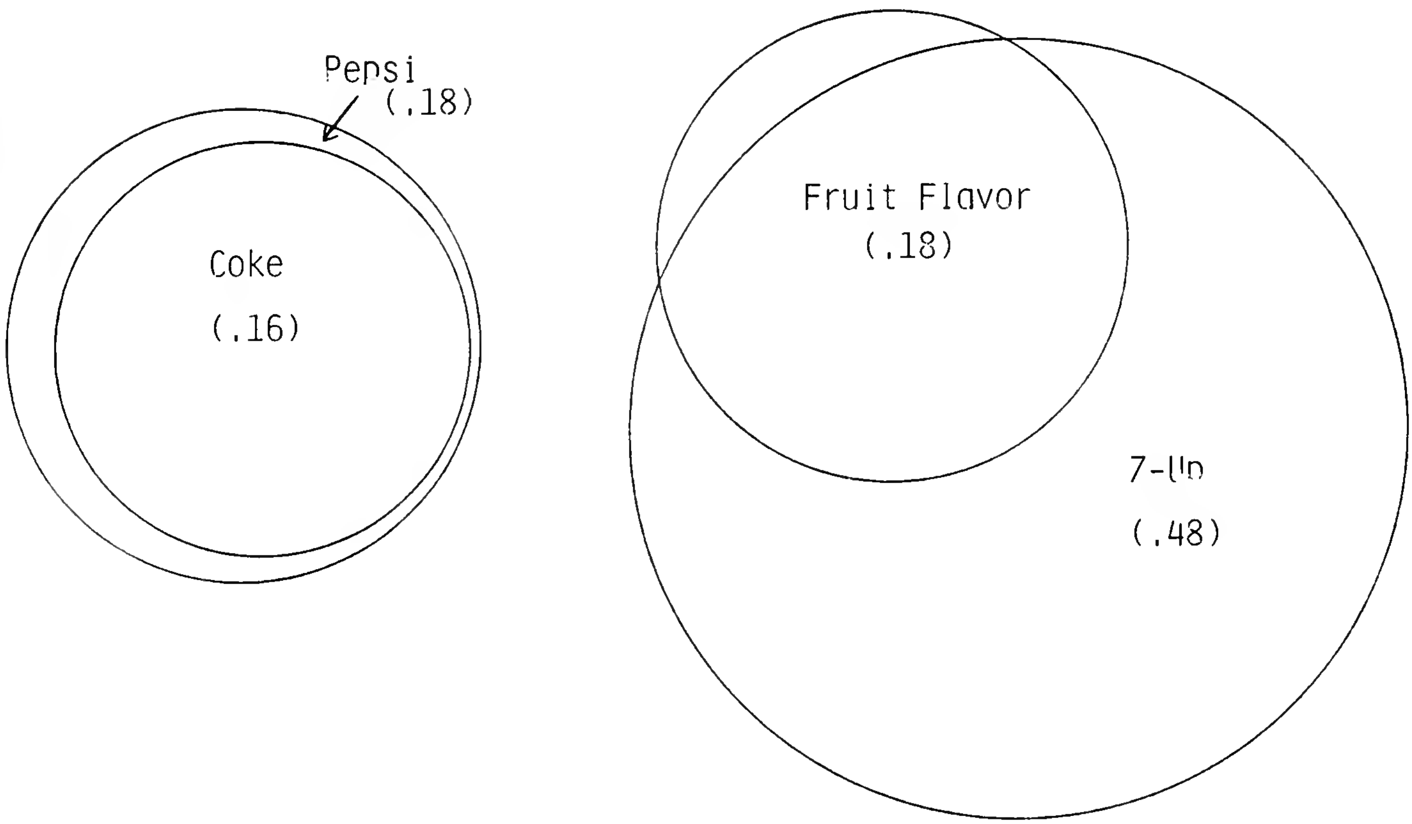


FIGURE 11:

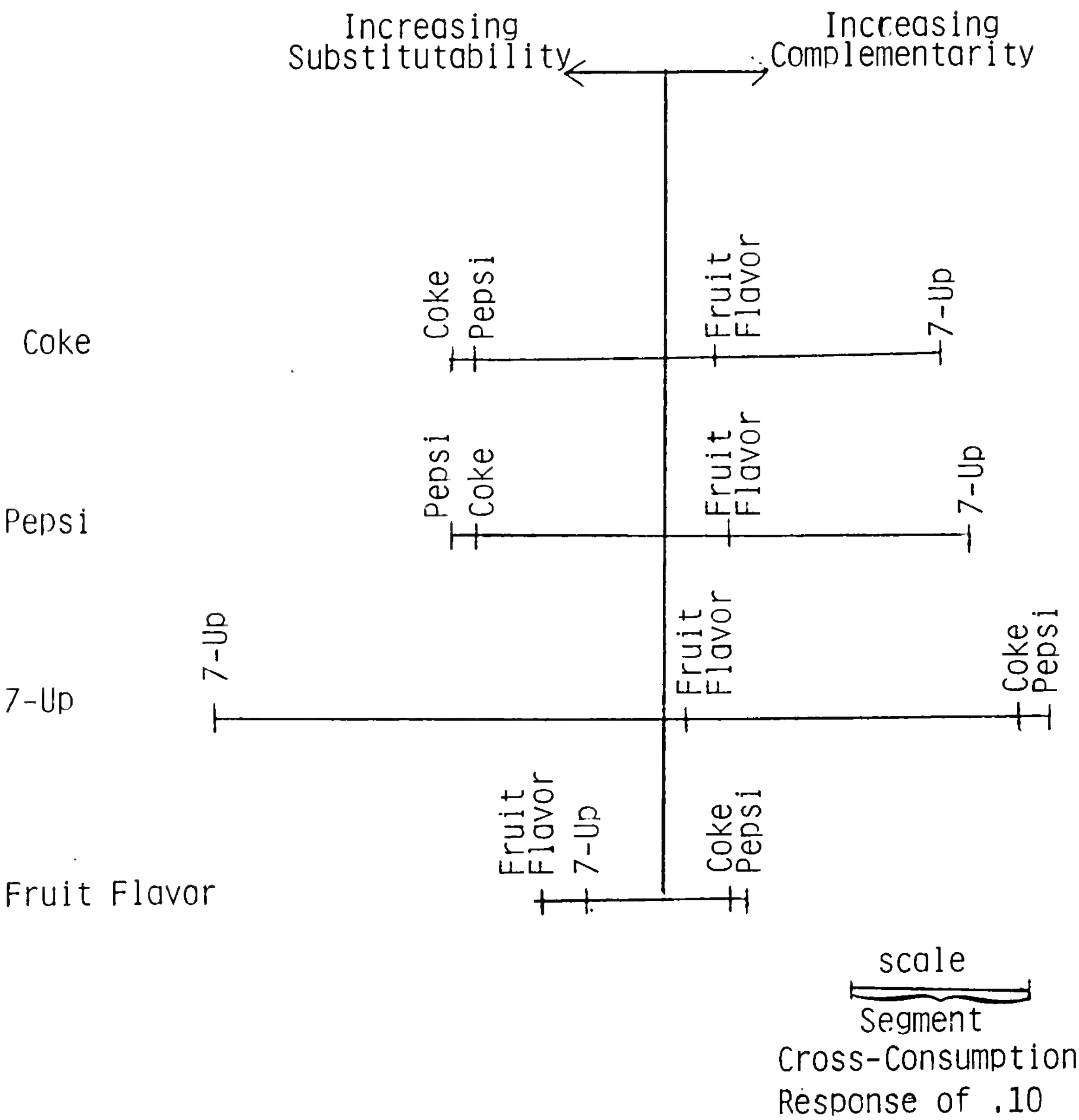
VENN DIAGRAM OF MARKET COMPOSITION
FOR THOSE TWO SUBJECTS WHO DRINK BOTH
7-UP AND FRUIT FLAVOR AND VIEW THEM AS SIMILAR



Brand	Preference for Brand in this segment	Brands Seen As Sharing an Aspect by this Segment	Value of Shared Aspect
Coke	.16	Coke and Pepsi	.16
Pepsi	.18	7-Up and Fruit Flavor	.17
7-Up	.48		
Fruit Flavor	.18		

FIGURE 12:

BRAND'S-EYE-VIEWS OF CROSS-CONSUMPTION RESPONSE
FOR THOSE TWO SUBJECTS WHO SEE 7-UP AND
FRUIT FLAVOR AS SIMILAR



reverse is not true. A variety seeker who had just consumed Fruit Flavor might find 7-Up's unique aspect very appealing. However, if that variety seeker had just consumed 7-Up, there would be very little unique about Fruit Flavor to attract her or him.

One final observation should be made. The size of the effect that a brand can have on other brands is a direct function of its relative preference (π_1^A). Notice that π_{Pepsi}^A is slightly larger than π_{Coke}^A in this segment. Correspondingly, Pepsi's complementary effect on 7-Up is slightly larger than Coke's. This also holds true for Pepsi's and Coke's complementary effects on Fruit Flavor. Notice that $\pi_{7\text{-}Up}^A$ is significantly larger than $\pi_{Fruit\ Flavor}^A$. These brand's complementary effects on Coke and Pepsi are similarly scaled. The converse of this effect can also be noted in Figure 12. The size of the effect that other brands can have on a particular brand is also a direct function of that brands relative preference.

We will examine one last segmentation scheme in our attempt to understand the competitive interrelationships among these brands.

<u>Analyses of the Segment Perceiving Coke and Pepsi as Similar and of the Segment Perceiving Coke and Pepsi as Dissimilar</u>. Figure 7 indicates that Coke and Pepsi are perceived, in aggregate, as having at last some similarity. It's impossible to determine from Figure 7 whether virtually everyone sees them as slightly similar or whether there is one segment that sees them as very similar and another that sees them as not similar at all. We go back to the $S_{Coke,\ Pepsi}^h$ to answer this question.

It turns out that there are three distinct segments. First, there are those (24% of the sample) who see Coke and Pepsi as similar. Second, there are those (28% of the sample) who drink both Coke and Pepsi but see them as

offering totally different aspects. Third, there are those (48% of the sample) who do not drink both Coke and Pepsi.

Coke and Pepsi are most vulnerable to one another among that 24% of the market who see Coke and Pepsi as similar. It is these individuals who are likely to substitute a Pepsi for a Coke or vice-versa. The 28% of the sample who choose both Coke and Pepsi, but see them as dissimilar, are unlikely to substitute one for the other. Their selection of a Pepsi or Coke will subsequently stimulate the desire for the other drink (for the sake of variety). We begin, therefore, by considering those individuals for whom $S^{h}_{\text{Coke, Pepsi}} > 0$.

[FIGURE 13 AND 14 ABOUT HERE]

As expected we see that Coke and Pepsi substitute for one another in this segment. Furthermore, Coke and Pepsi each complement 7-Up, Fruit Flavor and Tab and vice-versa. Tab and 7-Up compete as a change of pace for these drinks. And the asymmetric relationship between 7-Up and Fruit Flavor emerges again. There are few surprises here.

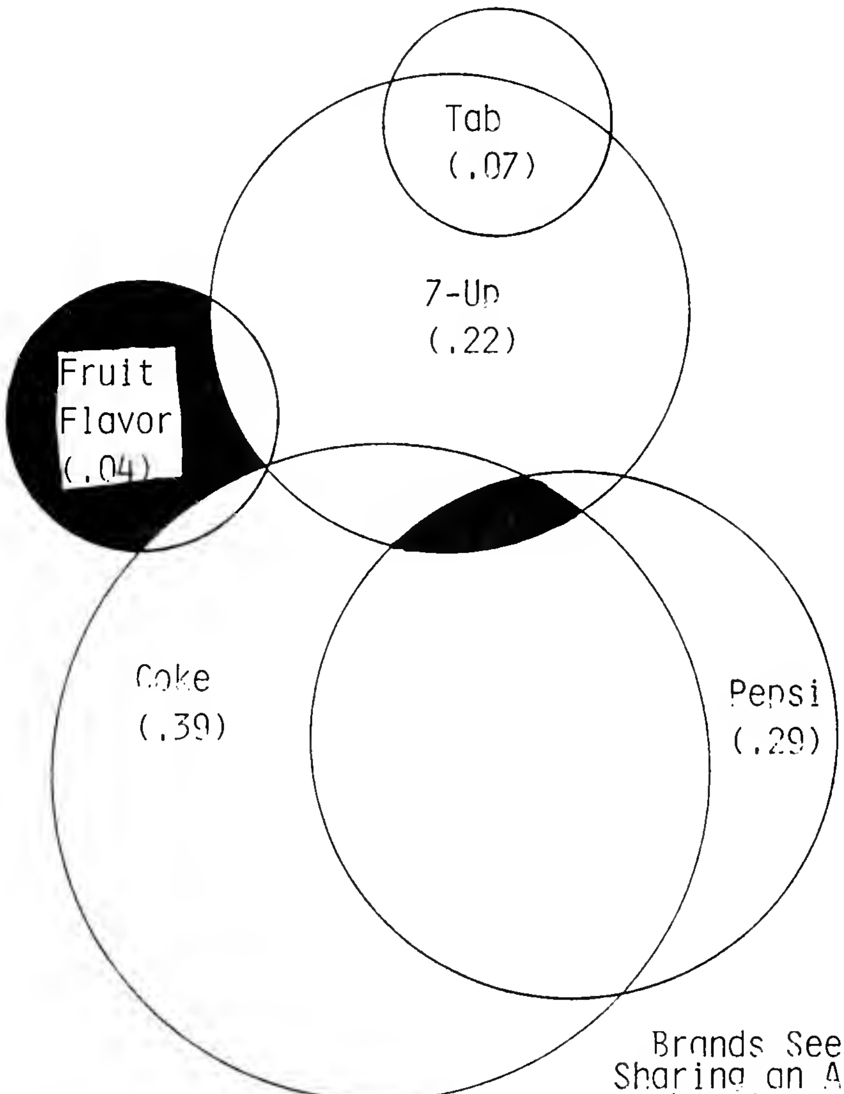
Let us now explore competitive interrelationships as perceived by the segment who drinks both Coke and Pepsi but sees them as dissimilar.

[FIGURES 15 AND 16 ABOUT HERE]

Figures 15 and 16 display the market composition and competitive interrelationships for that segment who drink both Coke and Pepsi but view them as dissimilar. These individuals are basically Coke drinkers. Pepsi commands very little preference in this segment. Due to a strong negative

FIGURE 13:

VENN DIAGRAM OF MARKET COMPOSITION FOR THOSE SEVEN SUBJECTS WHO DRINK BOTH COKE AND PEPSI AND VIEW THEM AS SIMILAR



Brand	Preference for Brand in this Segment
Coke	.39
Pepsi	.29
7-Up	.22
Tab	.07
Fruit Flavor	.04

Brands Seen As Sharing an Aspect this Segment	Value of Shared Aspect
Coke and Pepsi	.20
Coke and 7-Up	.03
Coke and Fruit Flavor	.02
Pepsi and 7-Up	.01
7-Up and Tab	.04
7-Up and Fruit Flavor	.03

FIGURE 14:

BRAND'S-EYE-VIEWS OF CROSS-CONSUMPTION RESPONSE
BASED ON THOSE SEVEN SUBJECTS WHO
SEE COKE AND PEPSI AS SIMILAR

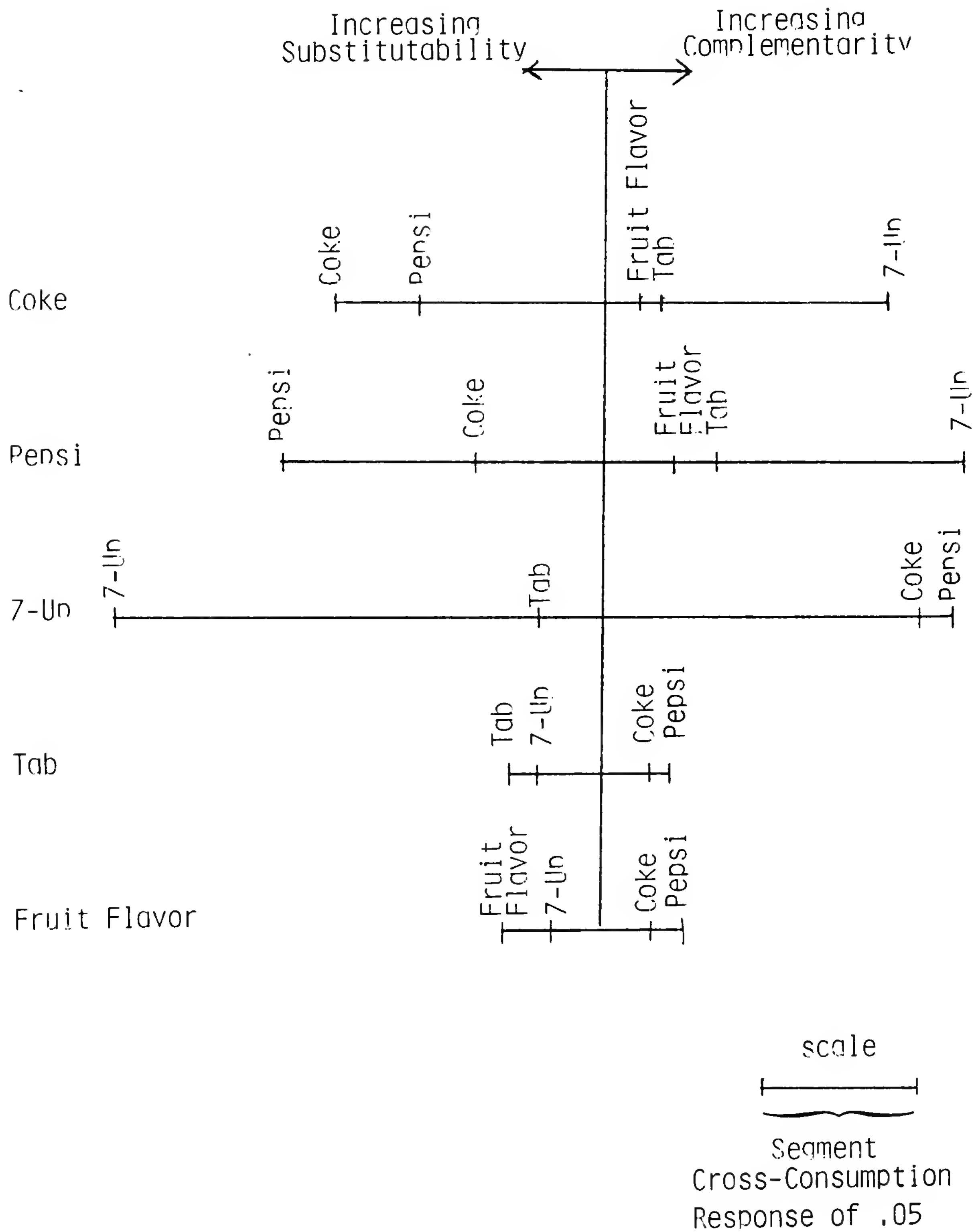
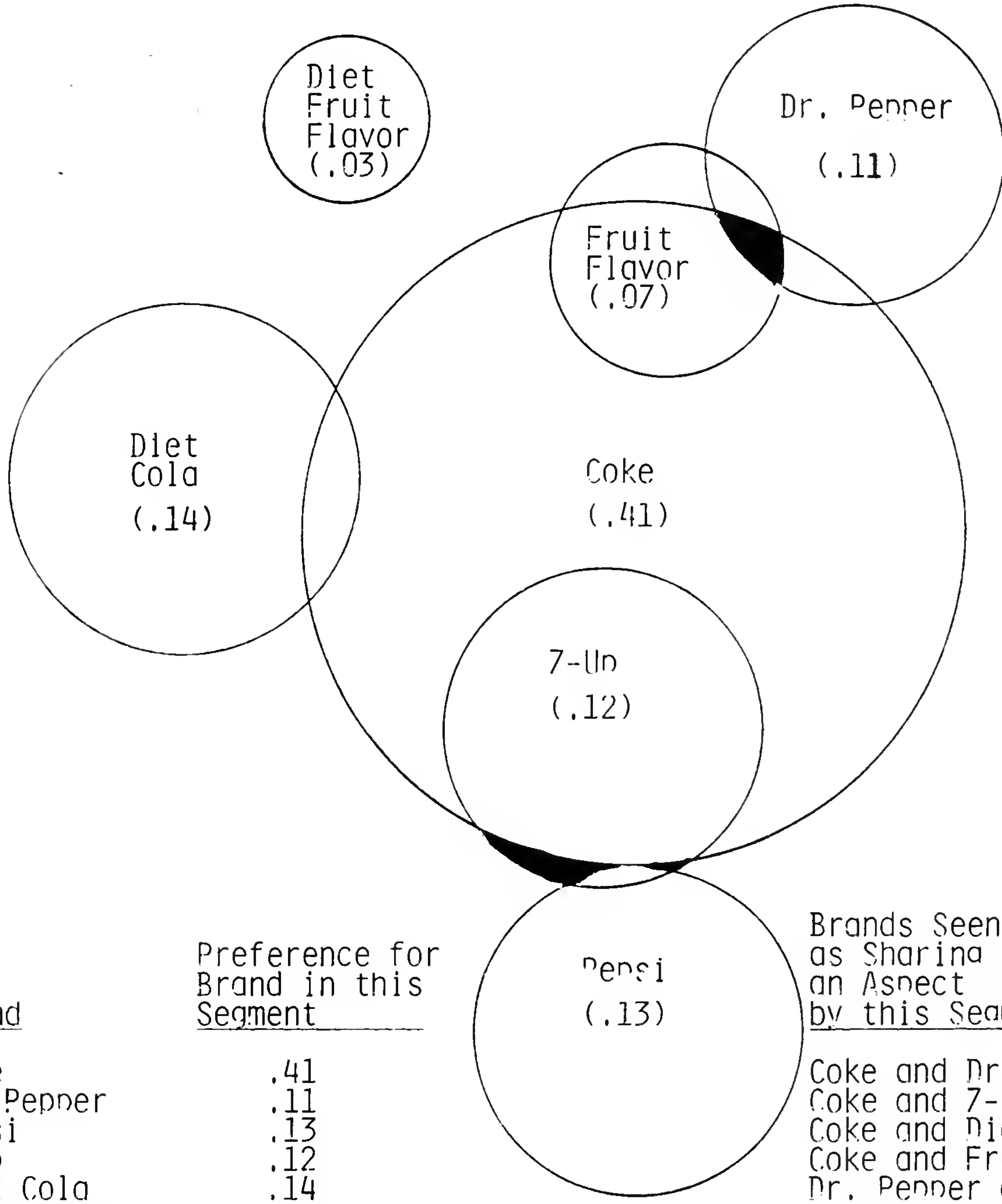


FIGURE 15:

VENN DIAGRAM OF MARKET COMPOSITION FOR
THOSE EIGHT SUBJECTS WHO DRINK BOTH
COKE AND PEPSI AND VIEW THEM AS DISSIMILAR

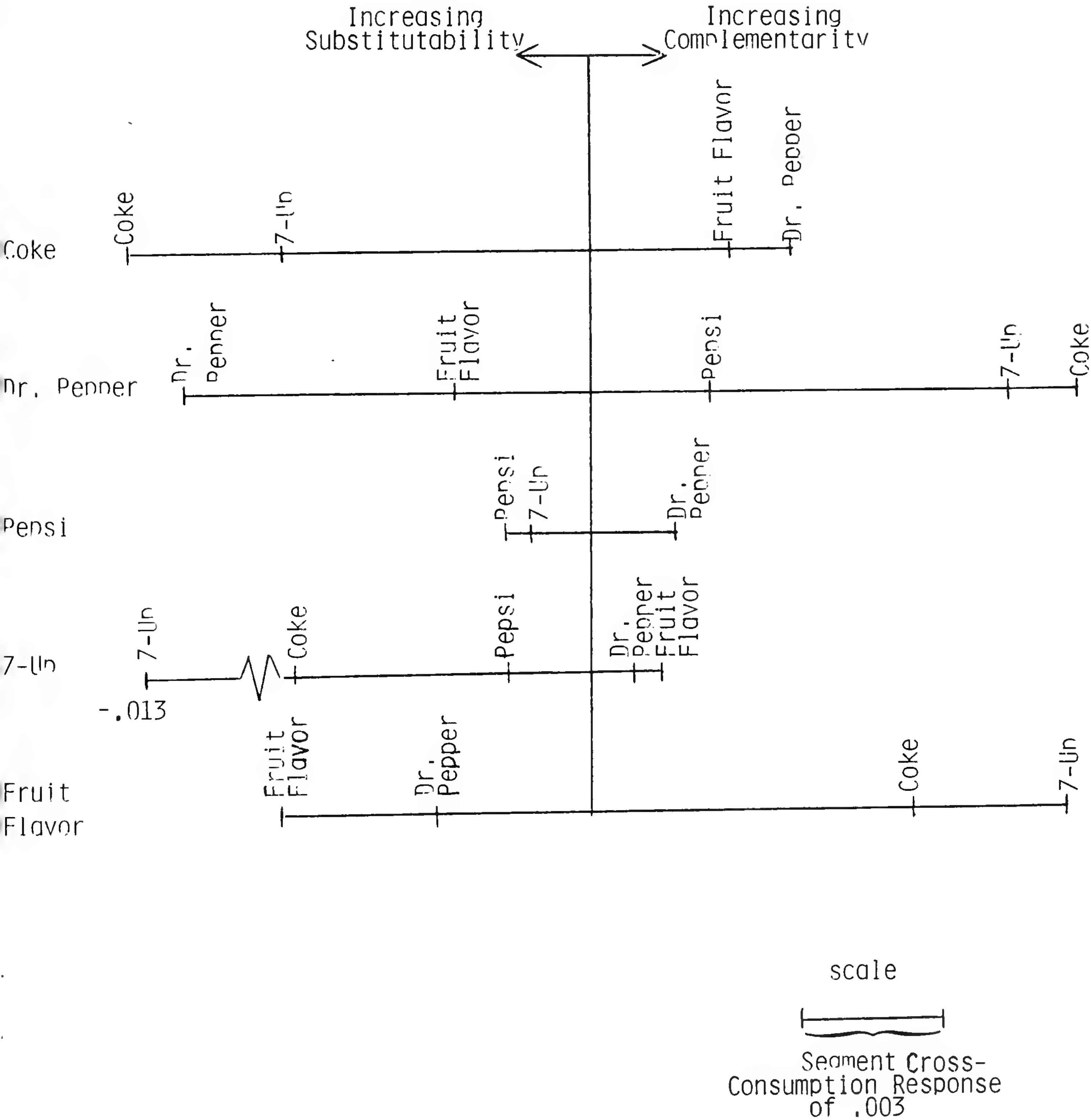


Brand	Preference for Brand in this Segment
Coke	.41
Dr. Pepper	.11
Pepsi	.13
7-Up	.12
Diet Cola	.14
Fruit Flavor	.07
Diet Fruit Flavor	.03

Brands Seen as Sharing an Aspect by this Segment	Value of Shared Aspect
Coke and Dr. Pepper	.02
Coke and 7-Up	.11
Coke and Diet Cola	.02
Coke and Fruit Flavor	.05
Dr. Pepper and Fruit Flavor	.01
Pepsi and 7-Up	.01

FIGURE 16:

BRAND'S-EYE-VIEWS OF CROSS-CONSUMPTION RESPONSE
BASED ON THOSE EIGHT SUBJECTS WHO DRINK COKE AND PEPSI
AND SEE THEM AS DISSIMILAR



correlation of preference for Coke and Pepsi across members of this segment, Coke and Pepsi neither substitute nor complement one another. 7-Up, in a surprising reversal from the previous segment analysis, substitutes for both Coke and Pepsi and vice-versa. Dr. Pepper and Non-Cola substitute for one another as they vie for the role of change of pace to Coke, Pepsi and 7-Up.

A very important difference between the Coke and Pepsi drinkers who see Coke and Pepsi as similar and those who see them as dissimilar is the relationship of 7-Up to those two drinks. The 24% of the sample who see Coke and Pepsi as substitutes view 7-Up as a complement to Coke and Pepsi. That 28% of the sample who see Coke and Pepsi as independent see 7-Up as a substitute for Coke and Pepsi.

In sum, we have found that, for the sample as a whole, diet drinks are largely competitively independent from non-diet drinks. Tab, an exception to this rule, interacts with both diet and non-diet drinks. We also uncovered the hypothesized complementarity that existing techniques were unable to identify. Among diet drinks cola drinks complement non-cola drinks. Among non-diet drinks there are three classes: "major colas," "major change of pace" and "minor change of pace." Brands within each class substitute for one another. Brands in different classes complement one another.

Through various segmentation analyses, we were able to recover certain effects washed out in aggregation. We found that Coke dominates most segments with other brands offering some measure of variety. An exception to this rule is segments in which Coke and Pepsi are perceived as approximately equally attractive and as being very similar. In a surprising reversal, 7-Up is seen as a complement to Coke and Pepsi by the segment who see Coke and Pepsi as similar. 7-Up is seen as a substitute for Coke and Pepsi by the segment who see Coke and Pepsi as dissimilar.

SUMMARY AND CONCLUSIONS

Existing techniques based on consumer choice (Hendry partitioning, Rao and Savala's hierarchical clustering and PRODEGY) were shown to produce limited results when used to infer competitive interrelationships among brands in a class in which variety seeking is an important determinant of consumer behavior. When applied to a collection of individual's soft drink consumption histories, these techniques were able to split the brands into two competitive subclasses: diet drinks and non-diet drinks. They were not, however, able to further split these subclasses into cola drinks and non-cola drinks. These techniques all assume that individuals switch between brands which are close substitutes. When consumers seek variety they are likely to switch between brands which complement one another. In our data, consumers frequently switched between cola drinks and non-cola drinks. The existing techniques inferred from those switches that cola drinks are the closest substitutes for non-cola drinks.

Using a model of variety seeking behavior (McAlister, 1983), we have developed a technique for revealing substitute and complementary relationships from brand switching data. We were able, as were existing techniques, to distinguish the relative competitive independence of diet soft drinks from non-diet soft drinks. By producing continuous values for degree of substitutability or complementarity rather than simply designating two products as competitors or not (as is done in a partitioning scheme), we were able to observe a subtle caveat to the diet/non-diet dichotomy. Tab, as one would expect, had competitive interactions with other diet soft drinks. It also had competitive interactions with non-diet soft drinks. It competed with 7-Up to be the "major change of pace" drink among the non-diet drinks. Partitioning techniques, with their requirement of placing a brand in one class or another, masked this subtlety.

Our technique, unlike existing techniques, was also able to reveal complementary relationships between cola drinks and non-cola drinks. Among diet drinks there was a simple complementary dichotomy. Among non-diet drinks there was a three-way complementarity among "major colas," "major change of pace" and "minor change of pace." Also, because of the continuous nature of our measure of complementarity we were able to show another subtle difference. Both Coke and Pepsi complement 7-Up and vice-versa. Pepsi, however, is a stronger complement to 7-Up than is Coke and 7-Up is a stronger complement to Pepsi than to Coke. Understanding the relative strength of the complementary relationships should enable managers to select partners for joint promotional efforts, to devise advertising themes and to arrange retail displays more effectively.

Our technique also allowed for asymmetric competitive relationships among brands. Asymmetry appeared in a segment of high intensity variety seekers who viewed 7-Up as providing everything that Fruit Flavor provided plus something unique to 7-Up. For these subjects 7-Up substituted for Fruit Flavor, while Fruit Flavor complemented 7-Up.

A further advantage of our technique follows from its retention of individual level information. Competitive interrelationships estimated for the total sample mask many interesting and managerially useful insights. By segmenting consumers on various managerially relevant dimensions we were able to recapture and explore competitive interrelationships which cancelled one another out in the total sample statistics. For example, we found that people who see Coke and Pepsi as similar view 7-Up as a complement to both Coke and Pepsi. Those people who see Coke and Pepsi as dissimilar view 7-Up as a competitor to both Coke and Pepsi.

In sum, we have proposed that for those product clases in which consumers seek variety, existing "behavioral" techniques cannot adequately

uncover competitive interrelationships. We have proposed a technique that goes beyond existing techniques to uncover complementarity among brands. Our technique also provides a continuum of values for substitute and complementary relationships. Further, it allows for asymmetries in competitive interrelationships. Finally, our technique is based on individual level information and can be disaggregated in any way and to any degree desired.

We claim no generalizability for these data. The sample was small and not representative. The object of this paper was to point out limitation of existing techniques and to propose a technique that overcomes that limitation. These data were sufficient for that task. The results are intuitively appealing and suggest that the estimation of this model on a large and representative sample might prove useful to managers.

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